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A BRAIN-COMPUTER INTERFACE TO CONTROL A PROSTHETIC HAND

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ABSTRACT

A Brain-Computer Interface (BCI) system was developed to operate a prosthetic hand and other devices. The Electroencephalogram (EEG) signals were recorded over the sensorimotor cortex area during foot, left or right hand motor imagery. Only two mental tasks and one or two EEG bipolar channels were identified and used in the online experiments. Autoregressive (AR) modeling was used to extract the features from the spontaneous EEG signals and Linear Discriminant Analysis (LDA) was used as the classifier.

Six subjects participated in the online study. However, only three subjects had sufficient control to proceed to the final application phase. The online classification errors for these subjects ranged between zero and 17.8% in the subject-training phase. In the application phase, the subjects were required to complete a preprogrammed test sequence. The optimal time to complete the test sequence is approximately 6 minutes. The times taken by the subjects to complete the test sequence were between 8 minutes 20 seconds and 17 minutes. The unintended activations per minute generated by the subjects varied from zero to 0.8 per minute.

In the present application, high classification accuracy with low unintended activations is more important than a high information transfer rate (ITR). By introducing thresholds in the LDA classification rule and averaging the LDA outputs over 5 seconds to arrive at a decision, we minimize the unintended activations although the true positives (TP) and the ITR were reduced. The results of the present study show that three of the subjects were able to use the BCI system to control a prosthetic hand and other devices.

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Yong Xin Yi

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LIST OF SYMBOLS AND ABBREVIATIONS

AAR	Adaptive Autoregressive
ADC	Analog-to-digital converter
AIC	Akaike's Information Criterion
ALS	Amyotrophic Lateral Sclerosis
AR	Autoregressive
b	LDA coefficients
BCI	Brain-Computer Interface
CR	Accuracy
CR_1	Classification accuracy of Feedback System 1
CR_2	Classification accuracy of Feedback System 2
CR_{ambi}	Percentage of the ambiguous classifications
CE_1	Classification error of Feedback System 1
CE_2	Classification error of Feedback System 2
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electroculogram
FA	Unsuccessful activation
FFT	Fast Fourier Transform
FN	False negative
FOOT/FEET	Imaginary foot movement
FP	False Positive
GUI	Graphical User Interface
IA	Intended activation
ITR	Information Transfer Rate

LDA	Linear Discriminant Analysis
LDA_{output}	LDA output of each sample
LEFT	Imaginary left hand movement
$mLDA_{output}$	Averaged LDA output of one trial
R^2	Coefficient of determination
RIGHT	Imaginary right hand movement
T_c	The duration of time to complete a test cycle
T_{low}	Lower threshold of the LDA
T_{min}	The optimal time to complete a test cycle
T_{NA}	The duration of time when the subject was not supposed to make any selection
TP	True Positive
T_s	The duration of time when the subject could make a selection
T_{up}	Upper threshold of the LDA
UIA	Unintended activation

CHAPTER 1
INTRODUCTION

CHAPTER 1 INTRODUCTION

1.1 Problem Statement

Research into how the EEG signals can be used as commands to communicate or to operate various assistive devices may improve the quality of life of patients with neurological disorders, the handicapped and other patients with limited mobility. For instances, the patients can express their wishes by using a spelling program, control various devices at their environment or operate a neuroprosthesis by using EEG signals. Moreover, by interfacing the BCI system to the web browser, they can get access to the internet that may provide shopping, entertainment, educational and even employment opportunities. It is also possible to use the BCI system to produce music and graphic arts.

For patients who are not completely paralyzed such as the amputees, even though they may be able to use the voice, eyes movements, or movements of some non-paralyzed part of the body such as shoulder to control a prosthesis or other assistive devices, the users are required to learn to use artificial commands for the intended movements. The use of EEG signals to determine intent may provide a more natural way to control these devices.

1.2 Aims and Contributions

1.2.1 General aim

The aim of this research project is to develop a BCI system that will allow the users to use scalp-EEG signals to control a prosthetic hand and other devices.

1.2.2 Specific aims

The main focus of the present study is to implement real-time signal processing and classification algorithms that are robust and with minimal unintended activations of the control devices. The specific aims of the dissertation are as follows:

1) To develop an experimental protocol and select the mental strategy to obtain useful EEG signals.
2) To perform offline analysis on the EEG signals to find the subject-specific EEG channels and mental tasks.
3) To implement signal processing and classification algorithms to process the EEG signals real-time.
4) To develop a Graphical User Interface (GUI) that provides feedback and selection menu to control a prosthetic hand and other devices.

1.2.3 Contributions

The contributions of the present study are as follows:-

1) A standard experimental protocol for a BCI system was developed.
2) Real-time processing algorithms that include artifacts rejection, feature extraction and classification were implemented.
3) A GUI was designed to enable the activation of 4 different prosthetic hand movements and 4 LEDs representing 4 different remote devices.

1.3 Literature Review

According to Vaughan *et al.* [1], there are three ways to restore impaired motor functions:-

i) Use the remaining voluntary muscles activities such as the eye, hand or forehead movements to give simple commands, to move a cursor for communication [2], to operate adaptive switches and scanning devices [3].

ii) Circumvent the breaks in neural pathways that control the paralyzed muscles. For example, the electrical stimuli can be used to produce contractions in paralyzed muscles to perform functional tasks such as hand grasp, standing and locomotion [4] or to control a prosthesis [5].

iii) Provides new communication channels to the brain by using a BCI system [6-10].

In the present study, the last category- a BCI system is used to restore the impaired functions. The remaining literature reviews are focus solely on the BCI systems.

1.3.1 BCI System

A BCI is defined as "a system for controlling a device, e.g. computer, wheelchair or a neuroprosthesis by human intentions, which does not depend on the brain's normal output pathways of peripheral nerves and muscles" [11]. *Figure 1.1* shows a model of a BCI system and *Table 1.1* describes the functions of each component.

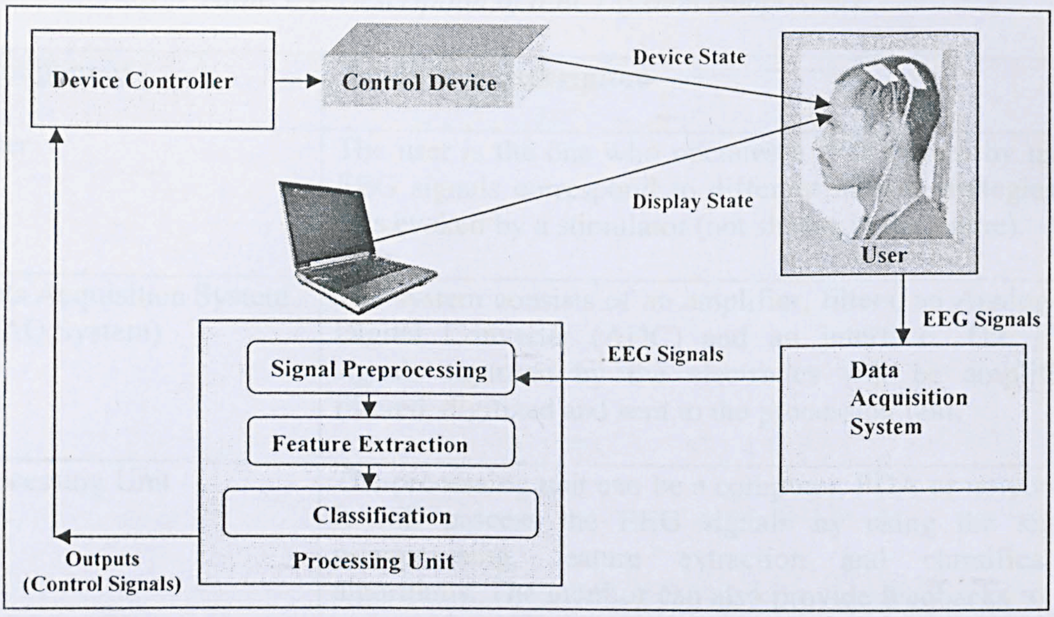


Figure 1.1. Model of a BCI system.

The different aspects that are important in the design of a BCI system are as follows:-

1) Target populations.
2) Intended applications.
3) The placement of the electrodes.
4) The type of the input brain signals to use (evoked potentials (EP), spontaneous EEG signals or neuronal action potential)
5) The mental strategy and training paradigm to use.
6) The operating mode (asynchronous or synchronous system)
7) The signal processing and classification methods

Table 1.1. Description of a BCI system components.

Component	Functional Description
User	The user is the one who operates a BCI system by using EEG signals correspond to different mental strategies or EPs evoked by a stimulator (not shown in the figure).
Data Acquisition System (DAQ System)	The system consists of an amplifier, filters, an Analog-to-Digital Converter (ADC) and an interface. The EEG signals captured by the electrodes will be amplified, filtered, digitized and sent to the processing unit.
Processing Unit	The processing unit can be a computer, PDA or notebook. It will process the EEG signals by using the signal preprocessing, feature extraction and classification algorithms. The monitor can also provide feedbacks to the user.
a)Signal Preprocessing	The raw signals will be preprocessed to increase the signal-to-noise ratio (SNR) of the EEG signals.
b)Feature Extraction	The algorithm will extract useful information from the EEG signals that correspond to different neurological mechanisms used by the user to control the BCI system.
c)Classification	The classifier will classify the features extracted. The outputs of the classifier (the control signals) will be sent to the device controller to control the device.
Device Controller	The controller will control the device.
Device	The control device can be a prosthetic hand, wheel-chair, switches to activate various home appliances and etc.

Table A.1 (Appendix A) shows the types of the existing BCI systems categorized based on the placement of the electrodes, the types of input brain signals they use and the operating mode of the system. The comparison of the characteristics and the performances of the BCI systems reviewed are presented in *Table A.2* (Appendix A). The characteristics include the frequency range of the EEG signals used in signal processing, the system sampling rate, the feedback update rate, the number of selections and the length of training time. Meanwhile, the performances of the systems are measured by using an accuracy rate that is obtained by evaluating the number of correct classification or the percentage of the true positive and false positive. The speed of the system is measured by using the information transfer rate (ITR).

1.3.2 BCI Target Populations

To date, most BCI groups focused mainly on the applications for people with little or no voluntary movement such as patients with Amyotrophic Lateral Sclerosis (ALS) [37], spinal cord injury [7,42,44-46], cerebral palsy [46] or locked in syndrome [39,47] who are unable to produce any type of motor output [1]. As BCI technology improves, it is expected to become useful to people who are less severely disabled, such as the handicapped who want to operate a wheelchair.

Several studies demonstrated that the ability of the healthy subjects and the disabled to operate the BCIs is the same [42,44,45,48 cited 49]. Studies have also shown that it is possible to discriminate two or three motor imagery tasks with the experiments conducted on healthy subjects [50] and spinal cord injury [7].

1.3.3 BCI Applications

BCIs can be used to control cursor movements to answer simple questions or to select items from a screen menu [6,7,36]. BCIs are also widely used to control a virtual keyboard to spell words and write messages [9,10,17,23,40,47]. Neuper *et al.*[51] described how a patient with infantile cerebral paresis used the Graz-BCI for verbal communication by using a telemonitoring system.

The BCIs can also be used to control devices such as neuroprosthesis [20,22,31], switches to control home appliances [13], functional electrical stimulator [14] and orthosis [52]. For instances, Graz BCI was used by a tetraplegic patient to use the orthosis to lift light-weighted objects and eat his first apple after 5 months of training with the BCI system [8,52].

Moreover, BCIs such as the Thought Translation Device (TTD) enables the patients to navigate the World Wide Web by using a web browser [18,19]. It is also possible to use a BCI in multimedia applications such as gaming [25]. There are BCIs that are used to control a mobile robot in a house-like environment [23] and control devices in a virtual apartment [53]. BCIs can also be useful in military applications. The Air Force Research Lab in USA [14] developed a Steady-State Visual Evoked Potential (SSVEP)-based BCI for flight simulator control to make faster response possible for the fighter pilot.

1.3.4 Electrodes Placements

Brain signals can be detected at all levels as shown in *Table 1.2*. Most BCIs developed are non-invasive in nature. It has relatively low spatial and frequency resolutions. It is also sensitive to noise. The voltage fields created by muscle and ocular activities are detectable all over the scalp and may contaminate certain parts of the useful EEG frequency range. Besides, the recording of the EEG signals require the placements of electrodes or electrode cap on the scalp of the subject. This causes variances in the recorded sessions during each use since it is not possible to place the electrodes at the same locations during each recording sessions.

Table 1.2. Various levels of the brain and the types of electrodes used to detect the brain signals.

	Different level of the brain	Types of electrodes used
Medically invasive	Immediately outside neurons and their synapses	Micro or semi-electrodes
	Surface of the brain	Subdural electrodes
	Just below the skull	Epidural electrodes
Medically non-invasive	Surface of the skull	Scalp electrodes

Meanwhile, there are a few BCI groups [29-33] currently developing invasive BCI systems because of the following advantages:

- The signals recorded are more stable and exhibit more detailed characteristics.
- The signals can be recorded at higher spatial and frequency resolution.
- The signals are free from muscle and movement artifacts and have higher SNR. Simpler processing algorithms can be applied on the signals.
- It provides a quick response time.

Despite the advantages of the invasive BCIs, non-invasive BCIs may prove as effective as that achieved with invasive BCIs. Pfurtscheller *et al*.[52] demonstrated that a quadriplegic patient fitted with a hand orthosis can learn to use motor imagery along with non-invasive BCI to open and close the orthosis. Moreover, the surgically implanted electrodes may present some risk of infection. These disadvantages can be overcome by using wireless radio frequency [54].

Since the BCI system developed is a scalp-EEG BCI system, the remaining reviews are focus solely on the scalp-EEG BCI system.

1.3.5 Types of Input Brain Signals (EPs vs Spontaneous EEG Signals)

EPs are brain potentials that can be evoked by a specific evoking stimulus while spontaneous EEG signals occur during normal brain function. Examples of spontaneous EEG signals are the μ and β rhythm [6,7,24], slow cortical potentials (SCPs) [19], the Bereitschaftspotential [25], the frontal β rhythm [20] and movement-related potentials of the 1-4 Hz frequency components [22]. *Table 1.3* compares the characteristics of the EPs-based BCI and the Spontaneous EEG-based BCI [1,15].

Table 1.3. Comparison of the EPs-based BCI and the Spontaneous EEG-based BCI.

	EPs	Spontaneous EEG Signals
Evoking stimuli	Required	Not required
Attention to the system	Demand attention to the stimuli. The user cannot pay attention to the environment	Do not demand the constant commitment of a sensory modality such as vision.
Timing of an action	Cannot be controlled	Can be controlled
Signal Processing	EPs focus on EEG activity that occurs at a specific time or specific frequency. The signal is stable and has high SNR. Hence, simple features such as the peak amplitude are used. However, averaging technique has to be used to process the signals.	Effort is required to recognize the EEG controls signals when the subject intends to activate the device. The EEG patterns may vary from days to days and has low SNR. Hence, more complex signal processing techniques are required.
Training time	The subjects do not need to be trained.	The subjects need to be trained.
ITR	Higher	Lower
Practicality	It is less practical since evoking stimuli is required. It can only provide discrete control	It is more convenient and more practical for individuals with impaired modalities. It can provide continuous control since the EEG signals obtained are ongoing.

1.3.6 Training Paradigm/ Mental Strategy

For the BCI systems that use spontaneous EEG signals as the input signals, the subjects have to be trained to use the system. Subjects have to produce and control changes in their EEG signals by performing certain mental tasks or concentrating on something when they undergo training in BCI experiments. Generally, there are two approaches used by the researchers to train the subjects to control the BCI systems:

1) Approach A: Subjects are trained to develop an automated skill of controlling certain EEG components such as

   - the μ rhythm (8-12 Hz) or β rhythms (20-24 Hz) generated in the sensorimotor cortex area and recorded over the central head regions [6,55 cited 56].
   - the β rhythm (25-28 Hz) recorded over the cortex's frontal areas [2].
   - the SCPs [47].

   The subjects were not instructed to perform any mental tasks but were asked to concentrate on moving the cursor [57 cited 58]. However, from the study, motor imagery was reported to be used frequently at the early training stage to produce and control the EEG activity. As the training progressed, the motor imagery may no longer be needed to control the EEG activity [6].

2) Approach B: Subjects are trained to control the EEG components by performing certain mental tasks. Motor imagery produces changes in EEG signals that have been well-studied and it has been used successfully in the BCI system [9,22-26]. Frequency components such as μ and β rhythm desynchronize or synchronize during movement preparation, execution and motor imagery such as left hand,

right hand and foot movements [24]. There are 4 ways in which the hand or foot imagery can be performed by the subject [59]:-

- Visualize his or her own hand/foot moving
- Visualize other's hand/foot moving
- Feel his or her hand/ foot moving (kinaesthetic imagery)
- Combination of visual and kinaesthetic imagery

Besides motor imagery, other mental tasks can also be distinguished and used in the BCI systems such as a mathematical task, a letter task, visual counting task and geometric figure rotation task [23]. The different EEG components and mental tasks used by various research groups are summarized in *Table 1.4*.

Table 1.4. EEG components and mental tasks used by various BCI groups.

BCI Groups	EEG components	Mental tasks	References
Graz-BCI	The mu rhythms (10-12 Hz) and beta rhythms (16-24 Hz) recorded over the sensorimotor cortex area.	Foot, right hand and left hand motor imagery	[9,24]
LF-ASD	The 1-4 Hz frequency band recorded over the motor cortex	Voluntary hand movements or finger flexions motor imagery	[22,60]
BBCI	The Bereitschaftspotential recorded over the primary motor cortex	Voluntary left and right hand movements	[25]
ABI	The EEG signals (8-30Hz) recorded over the 8 standard fronto-centro-parietal locations	Relax, right and left hand motor imagery, cube rotation, subtraction and word association	[23]
Oxford BCI	The EEG signals recorded over the sensorimotor motor cortex.	Two mental tasks (one used the motor imagery and one involved mental arithmetic) and a baseline task of relaxation	[26]

The possible advantage of automated skill (Approach A) is that it may only require little or no conscious effort once it becomes automatic [57]. For instance, Miner *et al.* [37] showed that the attention to auditory queries and formulation of answers does not interfere with the EEG-based cursor control. The complexity of the question also does not affect the performance of the subject [37]. However, the Approach B requires greater concentration and mental effort.

1.3.7 BCI Operating Mode (Synchronous vs Asynchronous BCI)

In a synchronous BCI, the period of control is initiated by the system while in an asynchronous BCI, the period of control is initiated by the user [41]. In a synchronous system, the signal will only be classified within the time window when a cue is given to the subject to perform certain mental task. This is useful for communication applications where the BCI is used repeatedly such as in spelling program [18,19]. In control applications such as in operating a neuroprosthesis, a user-initiated control (asynchronous system) is required. In an asynchronous BCI system, there is a period of idleness between two active control initiations when the user is in a mental state other than the mental state used to activate the system.

Several BCI groups have designed and tested asynchronous control applications. The LF-ASD BCI was designed to operate in asynchronous mode by discriminating attentive idle states and imagined finger movement [22]. Scherer *et al.*[9] used a different approach in implementing an asynchronous system for virtual keyboard application. In the system, three mental tasks (foot, right and left hand motor imagery) were discriminated and used to select the letters with the averaged spelling rate of 1.99 letters/min. The ABI is also an asynchronous BCI system used to control a robot and a virtual keyboard by using three mental tasks (left hand motor imagery, cube rotation and relax) [23].

1.3.8 Montage, Signal Preprocessing, Feature Extraction and Classification Methods

Different algorithms in processing the EEG signals are used due to the difference in the nature of the input signals, number of electrodes used and other characteristics. The spontaneous scalp-EEG signals were used as the input signals in the BCI system. Therefore, only the montage, signal processing and classification methods used in the Spontaneous EEG-based BCIs are reviewed and discussed in this section. The montage and the algorithms used by the various BCI groups for signal preprocessing, feature extraction and classification are reviewed and summarized in *Table A.3* (Appendix A).

1.3.8.1 Montage

The choice of the EEG channels used is important. The appropriate channels can be selected based on physiological justification or from various algorithms such as Common Spatial Pattern (CSP) [50] and Genetic Algorithm (GA) [48]. For some tasks such as the motor imagery, the recording positions are known. However, in the absence of prior knowledge about the spatial distribution of brain activity of a mental task, the algorithms to select the optimal recording positions are important.

1.3.8.2 Signal Preprocessing

Signal preprocessing such as Common Average Reference (CAR) and Laplace filter [7,70] may be useful to obtain optimal result and can increase the SNR. Three investigated preprocessing methods (common, local and average reference) [71] were shown to improve the classification results although not very significant. These signal preprocessing methods require more recording channels and therefore a greater number of electrodes.

1.3.8.3 Feature Extraction

Feature extraction is important in the process of classification because feature extraction reduces the data by measuring certain features of the signals, which capture the relevant information in discriminating the signals [72]. The different approaches used may have substantial effect on the accuracy of the classification results. *Table A.3* (Appendix A) shows the different algorithms used by the BCI groups to extract features from the EEG signals. AR or AAR modeling and the band power method are among the most commonly used algorithms.

The analysis of the EEG signals using AR in Fenwick *et al.* [73] showed that the model can be used to produce both ongoing EEG activity and EPs. AR can be a useful approach in determining the spectral properties of EEG [74]. Several BCI systems also used AR as a feature extraction method [6,67,69,72,75,72 cited 76, 77-80]. On the other hand, AAR has been used successfully as features to a linear classifier (LDA) to discriminate different motor imagery patterns [34,52].

AR is appropriate if the signal is stationary. It requires a number of samples data points to estimate the AR coefficients. Hence, when applying AR to biological signals like EEG, the signals are segmented and it is assumed that each segment of the signals is stationary. The shorter the segment used, the higher the time resolution and the less accurate the AR coefficients estimation. In AAR, the AR coefficients are estimated adaptively for every observation of the EEG signals and it requires no buffer memory and low computational effort. *Table 1.5* compares the properties of AR and AAR. Both of the AR and AAR share the following advantages [64,83]:-

- A limited number of parameters are sufficient to represent the EEG signals.
- No prior frequency selection is required.

- There is a unique optimum solution of AR parameters.
- Efficient algorithms are available to estimate the parameters.

Table 1.5. Comparison of AR and AAR.

	AR	**AAR**
Stationarity	Applied to stationary signals.	Can be applied to both stationary signals and non-stationary signals. The stochastic model describes well the random behaviour of the EEG.
Number of data points required to estimate the parameters	At least 100 [81].	The recursive nature of the algorithm enables the AR coefficients at a particular sample to be estimated from the previous data points [82].
Time resolution	Lower	High (Equal to the sampling rate).
Sensitivity towards noise	More robust	Very sensitive [61]
Real-time implementation	Require higher computational effort to obtain the same update rate as AAR [64,83].	Computational effort is low. The update rate is high. It is possible to provide feedback that is continuous in time and quantity by using the parameters [64,83].

The band power method used [7-9] is based on a band-pass filtering approach that describes the frequency-specific power changes of the ongoing EEG activity. AR or AAR estimation models the complete EEG signals. The comparison between the band power method and the AAR is shown in *Table 1.6*.

For the band power and AR or AAR methods, a small number of bipolar recordings were used. Another approach, CSP that reflects the specific activation of the cortical areas during hand motor imagery requires a greater number of electrodes than the other procedures and it also shows some sensitivity to the electrode montage [7].

Table 1.6. Comparison of the band power method and AAR.

	Band Power method	**AAR**
Algorithm complexity	Simple and efficient	More complex [61] (The AAR depends on the correct estimation of parameters such as the model order and the forgetting factor, which requires experience.)
Computational effort	Low	Low [64] (Only data recorded previously are required in the estimation.)
Influence of the artifacts	More robust [61].	Very sensitive [61] (Artifacts can cause the classification results to be biased and more training data must be used to set up the classifier.)
Prior subject specific frequency selection	Required (Feature selection algorithms such as GA [9] and Distinction Sensitive Learning Vector Quantization (DSLVQ) [62] are used to select the optimal frequency band for each subject.)	Not required [64]
Time resolution	Equal to the window size	Equal to the sampling rate

Short-time Fourier Transform (STFT) and classical approaches like periodogram contrary are not as widely used as band power method and AR or AAR. Classical spectrum estimation, implemented by using Fast Fourier Transform (FFT) is computationally efficient and produces reasonable results for a large class of signal processes. However, it has limited frequency resolution as stated in the Heseinberg Uncertainty Principle and it suffers from 'leakage' in the spectral domain because the sampled data is windowed [84]. AR power spectrum can give higher resolution than FFT analysis for short time segments and thus permits more rapid device control [6].

1.3.8.4 Classification

Prior to classification, most of the researchers will incorporate some feature selections technique such as GA, Principle Component Analysis (PCA), DSLVQ and others into the classifier in order to reduce the dimensionality of the features vectors and improve accuracy. For instance, GA was used to select the frequency band, the number of samples used for the averaging and the time within the motor imagery period [9]. It was also used to reduce the dimensionality of the features sets extracted from ECoG channels [85]; DSLVQ was used to select the subject specific frequency used in the band power method [34,62].

Each classification algorithms has its strengths and weaknesses, dependent on how we apply it, and the features we use. Generally, there are two categories of classifier: linear and non-linear classifiers. The choice of linear or nonlinear methods depends in the nature, size and other characteristics of the data set and requires a clear conception of the theoretical model being applied to the data [86]. If the data and knowledge about the data are limited, linear methods are preferred. However, if a large amount of data is available, non-linear methods are suitable to find the more complex structure in the data [86]. Both linear and non-linear methods are susceptible to outliers. Therefore, regularization used [38,87] can help to limit the influence of outliers or strong noise, the complexity of the classifier and the raggedness of decision surface in the classifiers [86]. *Table 1.7* compares the properties of the linear and non-linear classifiers.

Table 1.7. Comparison of the linear and non-linear classifiers.

	Linear Classifier	Non-linear Classifier
Assumptions	The data are linearly separable. Generally, assumptions about the distribution density functions of the pattern classes are made and the performance criterion is chosen [88].	No assumption about the distribution densities has to be made and it can utilize the training-set data directly in order to determine unknown coefficients of the decision rules [88].
Implementation	Easy and simple	More complex (The appropriate architecture of the network and the training parameters have to be chosen. Inappropriate design of the network may cause the network to overlearn or unable to classify new data [79].)
Robustness	More robust towards noise and outliers, and less prone to overfitting [86]	Experience devastating effects in the presence of noise and outliers, and more prone to overfitting [86]
Flexibility	Limited parameters to tune	Many parameters to tune
Computation time and memory	Low	High (The training process is long and has to be stopped arbitrary in certain cases [79].
Training set size	Small	Big
Examples	1) LDA 2) Signal Space Projection 3) Threshold method	1) Artificial Neural Network (ANN) such as the backpropagation neural network, Learning Vector Quantization (LVQ) 2) Support Vector Machines (SVP) 3) Local Neural Classifier

Linear classifier such as LDA is the most widely used classifiers in the BCI systems [7-9,25,38,40,61] because of its speed of computation and minimal loss in performance. The high-dimensional and noisy nature of EEG may limit the advantage of nonlinear classification methods over linear ones. A linear classifier (LDA) and two nonlinear classifiers (neural networks and support vector machines) were used to classify five mental tasks [79]. The nonlinear classifiers only produce insignificant improvement in the accuracy [79].

In the Graz BCI system, LVQ is mainly applied to online experiments with delayed feedback presentation, that is, the feedback was provided at the end of each trial; LDA is usually applied on the online experiments with continuous feedback presentation [7]. The study also shows that a smaller number of training trials (160 trials) is needed to set up a suitable classifier online by using LDA compared to LVQ.

Another classification approach such as the Hidden Markov Models (HMM) trained with Hjorth parameters was used because it can model the dynamic EEG changes that will not be considered in the classification methods based on AR or CSP such as LDA [8].

SVMs involve fewer parameters than neural networks, have built-in regularization and are extremely fast [79]. It guarantees to find the optimal decision function for a set of training data.

In a BCI system, the classifier will usually be updated after three to five sessions to improve the classification accuracy in the course of experiments [62]. An interesting approach, Adaptive Quadratic Discriminant Analysis [65] was developed to automatically adapt to the subject when there is a change in his or her EEG signals.

1.4 The Present BCI System

In this section, the BCI system that is developed at the Biomedical Engineering, University of Malaya is introduced. The BCI system is still at the early stage of development. The goal of this research is to provide a means to the handicapped to use the EEG signals to control a prosthetic hand and other devices.

1.4.1 Electrodes Placements

The use of implanted electrodes in the brain requires a willing subject and a qualified neurosurgeon to carry out the operation. EEG electrodes that are placed at the scalp are easier to apply and the subjects are easier to get. Besides, many research groups [6-10,22,23] have successfully used the scalp-EEG for their BCI systems. Therefore, the BCI system uses EEG electrodes placed on the scalp.

1.4.2 Input Brain Signals

Spontaneous EEG signals (occur during motor imagery) are used as the input signals to the BCI system. The user can have voluntary control over the prosthetic hand or other control devices. The user can pay attention to his or her environment and no stimulus is required.

1.4.3 Mental Strategy

The mental strategy used in the present study is motor imagery, that is, the user has to imagine foot, right hand or left hand movements to operate the system. The approach of training the subject to regulate EEG signals is not used because it is time-consuming to train the subject to regulate the EEG signals based on the feedback training. Motor imagery is used because it has been used successfully in several existing

BCI systems [8,9,23,26,61]. Moreover, in this approach, there is mutual learning between the subjects and the computer. Hence, the subjects are likely to gain control of the BCIs in a shorter time.

1.4.4 The Operating Mode

The system is designed to classify the ongoing EEG signals continuously. The subject will self-initiate and decide when to move the prosthetic hand or to select a remote control device by using the selection menu designed. Delay may occur in the generation of an appropriate change in the EEG signal and also in the process of translating the EEG signals to control signals.

1.4.5 Montage

Motor imagery is used in the training paradigm. Hence, bipolar EEG channels are derived from the electrodes placed over the foot and hand sensorimotor representation areas of the cortex. The montage used is based on the studies in Scherer *et al.*[9] and Guger *et al.*[61]. It was shown that 93% of the 99 subjects that participated in a field study were able to achieve accuracy of more than 60% after 20-30 minutes of training with just two bipolar EEG channels [61]. Hence, only one or two bipolar EEG channels are identified and used in the online experiments.

1.4.6 Signal Preprocessing Method

In practical applications, it is desirable to have as few scalp electrodes as possible. In the BCI system, only one or two EEG bipolar channels are used. Therefore, the spatial filtering algorithms are not considered since the algorithms require a greater number of electrodes. Temporal filtering is used. The raw EEG signals are band pass filtered from 5 to 40Hz to increase the SNR.

1.4.7 Feature Extraction Method

AR is used in this study to extract features from the EEG signals. AR power spectrum in the R^2 spectral analysis is also used to study the subjects' discriminating features. The motivations of using AR are as follows:-

- Simple and efficient algorithms exist to estimate the coefficients.
- A small number of bipolar electrodes are sufficient as compared to other approaches such as CSP [7].
- AR process can represent the short-term EEG spectrum with reasonable accuracy. Good spectral estimates can be obtained from short EEG segments.
- Only a few coefficients are required to represent the signals of interests.
- No prior selection of specific frequency band is required [34].
- The AR power spectrum estimation avoids the problem of leakage and provides better frequency resolution than the FFT-based methods [84].

AAR was not used in the present study despites its advantages discussed in Section 1.3.8.3 because it is more sensitive towards noise, more complex and the selection of the parameters such as the forgetting factor in the algorithm requires experience.

It is important to note that the main focus in the early development of the BCI system is to minimize the classification error. AR is used in the present study even though it has a longer feedback delay because a shorter feedback delay may cause instability and degrade the system robustness towards noise.

1.4.8 Features Selection Method

The selection of the EEG channels and the mental tasks combination to be used in the online experiments is based on the results of the averaged accuracy of the LDA 10x10 fold cross validation. Other methods such as GA are not considered because the dimensionality of the feature sets and the possible combinations of the features are not big. Simple algorithm like the LDA 10x10 fold cross validation is efficient and is possible to be implemented online.

1.4.9 Classification Method

A linear classifier is generally simpler and more robust than a nonlinear classifier [86]. Fisher's LDA is a linear classifier and is widely used. Hence, the method is used in the present study to classify the EEG signals online. The motivations of using LDA are as follows:

- It is simple and the weight vector can be easily obtained [64]. Hence, the classifier can be set up after the training data are obtained from the subjects and the new experiments can be performed immediately.
- Training time is short. It does not involve the long training procedure needed to adequately estimate the parameters for a neural network classifier [89]
- Smaller number of training sets is required [7].
- It has been used successfully in other BCIs [50].

1.4.10 The BCI Applications and System Configurations

The user can use the BCI system to select the desired type of prosthetic hand movements (grasp, key pinch, pulp-to-pulp pinch and tripod) and to reset the prosthetic hand. The different types of prosthetic hand movements are shown in *Figure 1.2*. The user can also select 4 LEDs representing 4 different devices.

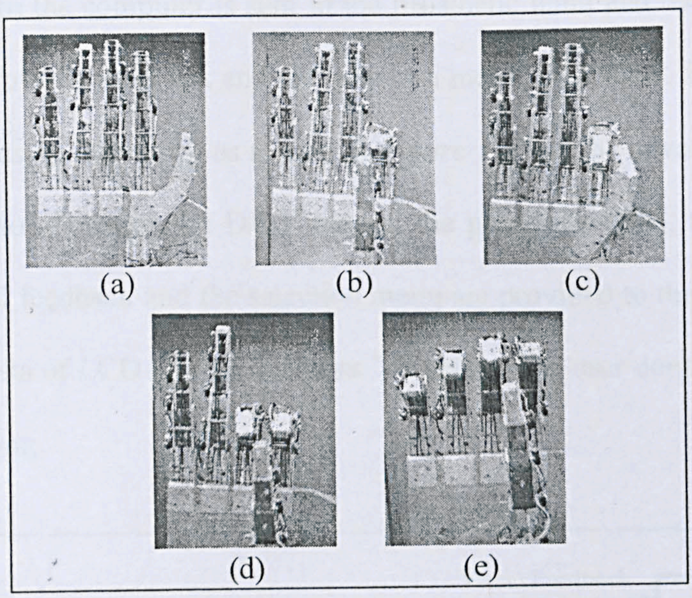


Figure 1.2. The different types of prosthetic hand movements that can be selected by the user: (a) Reset; (b) Pulp-to-pulp pinch; (c) Key pinch; (d) Tripod; and (e) Grasp.

The raw EEG signals collected will be filtered by an IIR elliptic band-pass filter (5-40 Hz), processed by AR algorithm and finally classified by a linear classifier using LDA. The LDA will continuously classify the EEG signals acquired from the user. The GUI and the algorithms used to process the EEG signals are developed in Visual C++, Microsoft Foundation Class (MFC) language.

To date, two systems have been set up: one using Universal Serial Bus (USB) communication and another one using wireless communication (Bluetooth). *Figure 1.3* shows the BCI system configurations using the USB communication and *Figure 1.4* shows the BCI system configurations using Bluetooth.

As shown in *Figure 1.3*, the BCI system consists of a computer, a BCI box, a prosthetic hand and 4 LEDs (represent 4 different switches to activate various devices). The EEG signals captured by the electrodes are amplified and filtered by the biosignal amplifier, digitized by an ADC, sent to the computer for further processing via the USB communication. By using the same USB data acquisition controller, the output decision of the classifier in the computer is sent to the prosthetic hand and the LED lights. The computer also provides feedback and the selection menu to the user. However, wireless communication using Bluetooth as shown in *Figure 1.4* has the advantage that there is no wire connection between the DAQ system, the prosthetic hand, the LEDs and the computer. Visual feedback and the selection menu are provided to the user by a display board that consists of LCD and LED arrays. Therefore, the user does not have to carry the computer along.

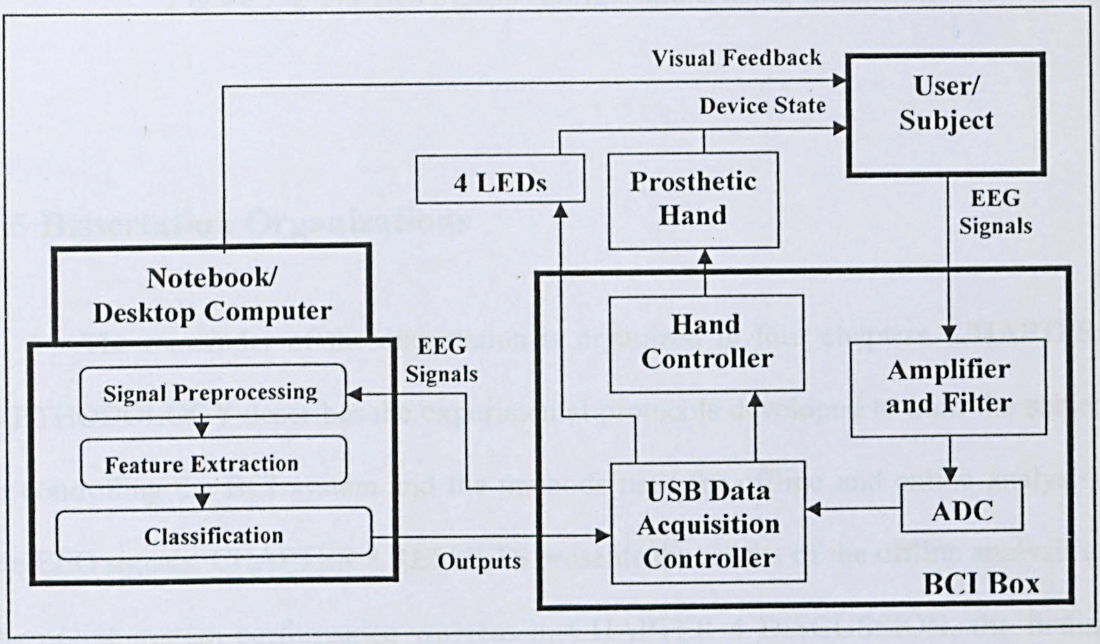


Figure 1.3. The BCI system configurations using USB communication.

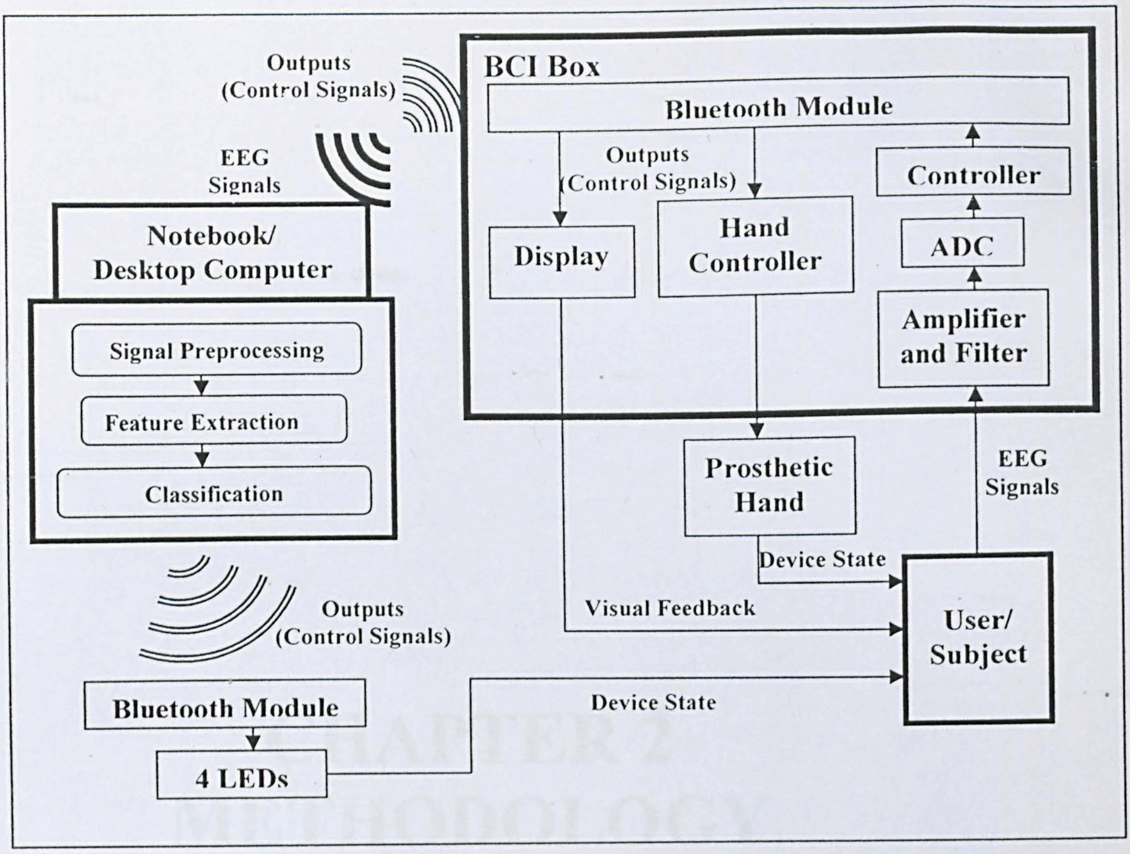


Figure 1.4. The BCI system configurations using Bluetooth.

1.5 Dissertation Organizations

The remainder of the dissertation is organized in four chapters. CHAPTER 2 METHODOLOGY describes the experimental protocols developed to train the subjects in controlling the BCI system and the methods used for offline and online analysis of the EEG signals. CHAPTER 3 RESULTS presents the results of the offline analysis and the online system performance whereas in CHAPTER 4 DISCUSSION, the findings and the system performance are presented. Finally, CHAPTER 5 CONCLUSIONS will summarize the findings and outline future research efforts and the area in which the system can be improved.

CHAPTER 2
METHODOLOGY

CHAPTER 2 METHODOLOGY

In this chapter, the experimental protocols developed, the BCI system design and the methods used for offline and online analysis of the EEG signals are described. The subsections discussed in this chapter are shown in *Figure 2.1.*

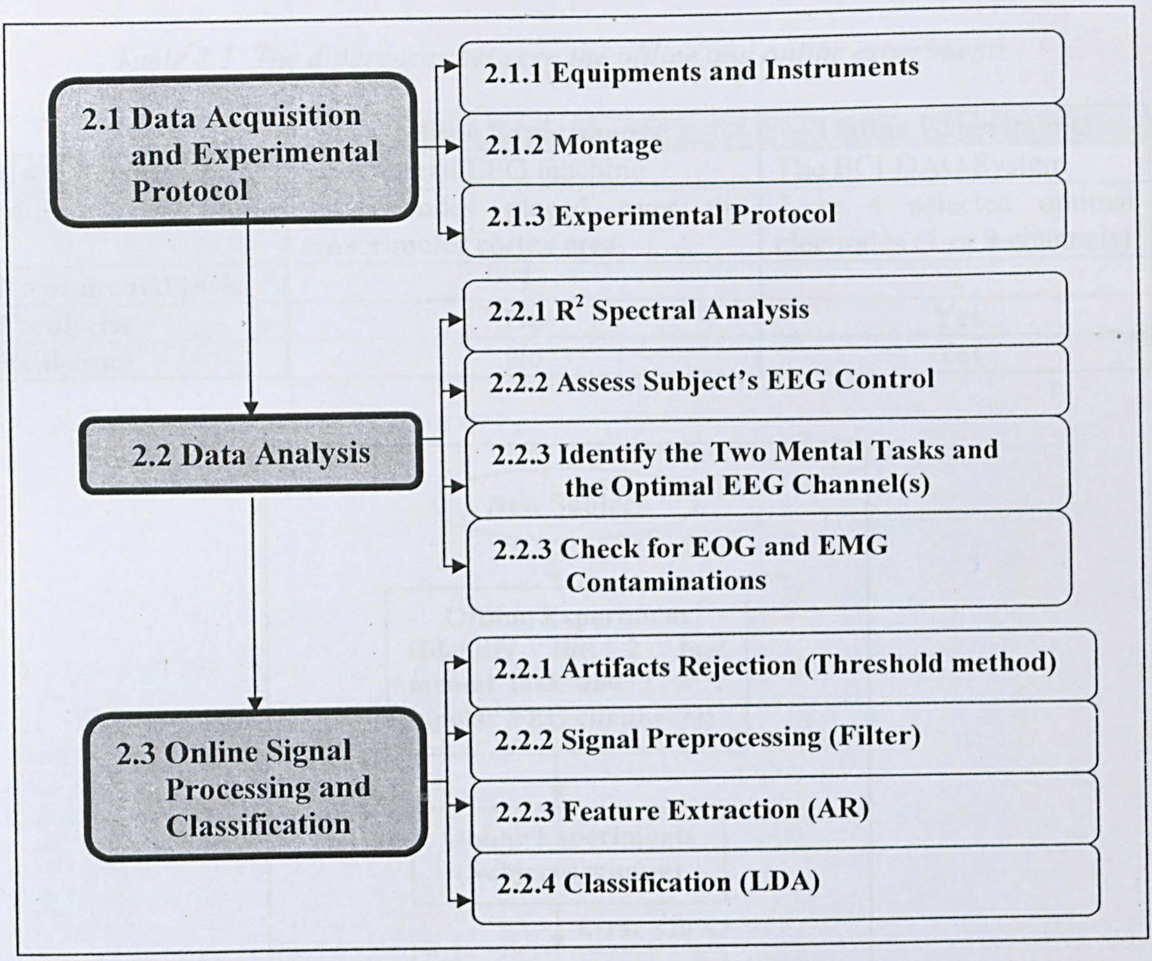


Figure 2.1. The subsections in CHAPTER 2 METHODOLOGY.

2.1 Data Acquisition and Experimental Protocol

Two types of experiments are conducted on the subjects: the offline experiments to collect the EEG trials for data analysis and the online experiments to train the subject to use the BCI system. The differences between these two types of experiments are described in *Table 2.1*. The flow of the experimental protocol conducted on a subject is summarized in *Figure 2.2*. After an offline experiment, the EEG trials are analyzed to identify the best two mental tasks and the EEG channels to be used for each subject in the online experiments. Next, the subject is trained to use the online system. Once the classification error of less than 20% can be achieved, the subject will use the application-based system to control the prosthetic hand and the LEDs.

Table 2.1. The differences between the offline and online experiments.

	Offline Experiments	**Online Experiments**
DAQ System	Commercial EEG machine	The BCI DAQ System
Montage	9 electrodes placed over the sensorimotor cortex area	2 or 4 selected optimal electrodes (1 or 2 channels)
No of mental tasks	3	2
Feedback	No	Yes
Real-time	No	Yes

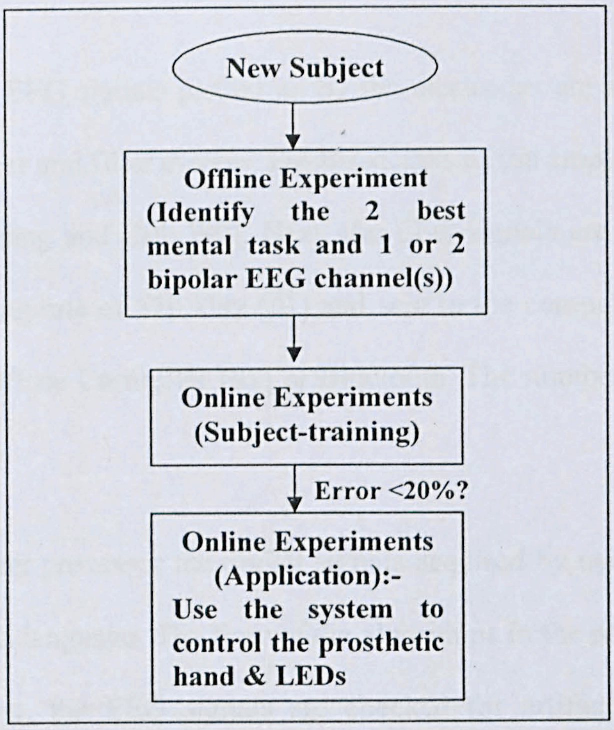


Figure 2.2. The flow of the experimental protocol performed on every subject.

2.1.1 Equipments and Instruments

2.1.1.1 Commercial EEG System

A commercial EEG system, the Medelec Profile Multimedia EEG system was used in the offline experiments. The system can support up to 32 EEG channels. The sampling rate of 256 Hz was used in this study.

2.1.1.2 The BCI Data Acquisition System

The block diagram of the system configuration of the BCI system using the USB and Bluetooth interfaces are shown in *Figure 1.3* and *Figure 1.4* respectively. The system can support four bipolar channels: two EEG channels, one Electroculogram (EOG) channel and one Electromyogram (EMG) channel.

The analog EEG signals picked up by the electrodes are amplified and filtered by the EEG amplifier and filter system. Further details of the amplifier and filter system can be found in Phang and Goh [90]. Next, the EEG signals are digitized by a 16-bit ADC at the sampling rate of 570 kHz [91] and sent to the computer batch-by-batch by using the USB Interface Controller [91] or Bluetooth. The number of observations in a batch of data is 256.

The computer processes the digital signals acquired by using a program written in Visual C++ MFC language. The flow of the algorithms in the program is summarized in *Figure 2.3*. First, the EEG signals are checked for artifacts (except during the application phase), filtered, modeled by AR and classified by LDA. The LDA output is used to move the cursor in the GUI to provide feedback to the user. During the application phase, control signals are generated by the computer and sent to the LEDs or the prosthetic hand controller to control the prosthetic hand. Further details on how a user used the GUI to activate the LEDs and the different prosthetic hand movements are discussed in Section 2.1.3.2 (C).

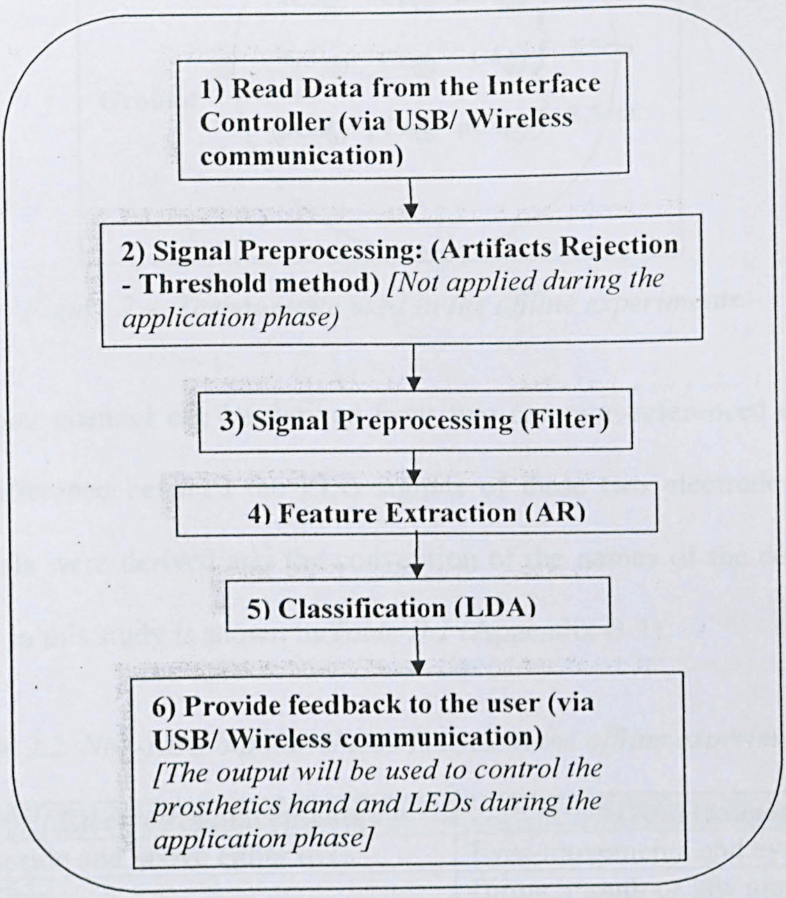


Figure 2.3. The flow of the computer processing algorithms in the BCI system.

2.1.2 Montage

2.1.2.1 Offline Experiments

The montage shown in *Figure 2.4* was used. Nine electrodes were placed over the sensorimotor cortex area. All the electrodes were referenced to an electrode placed on the forehead of the subject. The ground electrode was placed on the subject's mastoid (right or left) to prevent charge accumulation and reduce interference. Other non-EEG bipolar channels recorded along with the EEG signals to detect artifacts are described in *Table 2.2*. The use of the right hand and left hand EMG was an important measure to ensure that the subject did not move his or her hand during motor imagery.

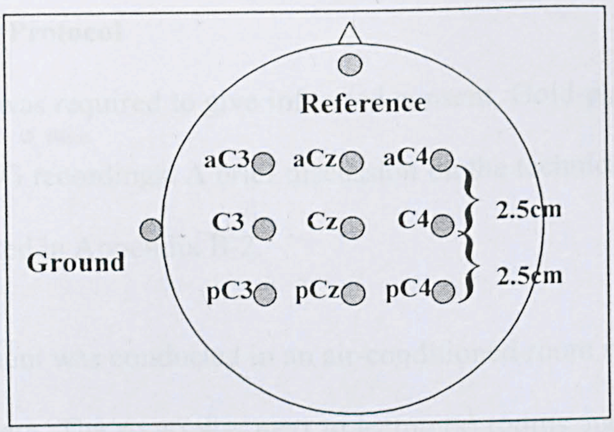


Figure 2.4. The montage used in the offline experiments.

A bipolar channel can be derived from two common-referenced electrodes by finding the difference between the EEG signals of these two electrodes. Nine EEG bipolar channels were derived and the convention of the names of the derived bipolar channels used in this study is shown in *Table B.1* (Appendix B-1).

Table 2.2. Non-EEG bipolar channels used in the offline experiments.

Channels	Electrodes placements	Artifacts detected
EOG	Beside and above either eyes	Eyes-movements and eyes-blinks
EMG	Chin	Biting, mouth or jaw movements
EMGs	Flexor and extensor digitorium communis of the right and left hand	Right and left hand movements

2.1.2.2 Online Experiments

Only one or two out of the nine bipolar EEG channels derived were identified (Section 2.2.3) and used in the online experiments. Besides the selected EEG channels, a ground electrode was placed at the mastoid. The EOG and chin EMG signals were also recorded online to detect artifacts.

2.1.3 Experimental Protocol

The subject was required to give informed consent. Gold-plated scalp electrodes were used in the EEG recordings. A brief discussion on the technical applications of the electrodes is presented in Appendix B-2.

The experiment was conducted in an air-conditioned room without any shielding or sound-proof system. The room was next to lecturers' rooms and near the main road of the university. Therefore, the subject was exposed to noise from the traffics, telephones ringing and conversations.

The subject was seated comfortably on a chair with the visual display placed approximately 100cm in front of the subject. The subject was required to perform two or three of the following mental tasks: imaginary right hand movement (RIGHT), imaginary left hand movement (LEFT) and imaginary both feet movement (FOOT). Throughout the offline and online experiments, several commands were given to the subject. The details on what the subject should do when the commands were given are described in *Table 2.3*.

Table 2.3. Details on what the subject should do when different commands were given.

Command	Task to perform
REST	Rest and relax. Subject can blink his or her eyes and stretch the body.
READY-RIGHT or READY-LEFT or READY-FOOT or READY-TONGUE	Decide which mental task to perform and prepare to imagine. This will help to prevent the subject from performing the wrong task. Based on past experience, the subject would sometimes perform the wrong task without this command.
RIGHT	Imagine right hand to move repetitively.
LEFT	Imagine left hand to move repetitively.
FOOT	Imagine both feet to move repetitively.

2.1.3.1 Offline Experiments

Before an experiment, the experimental protocol was explained to the new subject. The details of the explanations are presented in Appendix B-3.

The experiment lasted for approximately an hour. It consisted of a repetitive process of RIGHT, LEFT and FOOT trials and the sequence of the mental tasks was randomized by the computer to avoid adaptation. The command was displayed on the GUI as shown in *Figure 2.5*. The feedback (cursor) in the GUI was used only during the online experiments.

The experiment paradigm is shown in *Figure B.2* (Appendix B-4). Five sessions were conducted in each experiment. Each session consisted of 30 trials (10 trials for each mental task) that lasted for about 9 minutes. Each trial lasted for 8 seconds. It started off with the command of READY-LEFT, READY-RIGHT or READY-FOOT. After 3 seconds, the command of LEFT, RIGHT or FOOT followed. After 5 seconds, the command of REST would be given. The resting interval between two consecutive trials varied randomly between 5 to10 seconds to avoid adaptation [34]. The paradigm for one trial is shown in *Figure 2.6*.

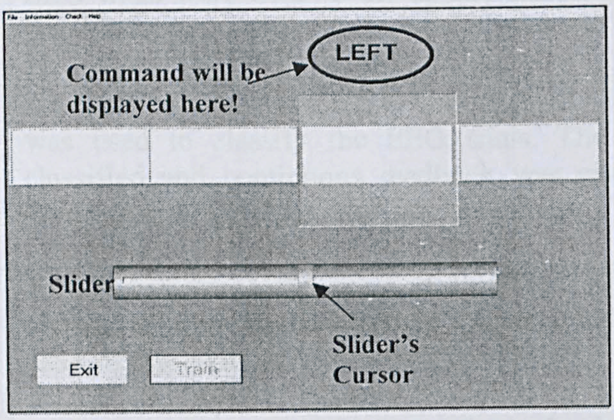


Figure 2.5. The GUI used in the experiments.

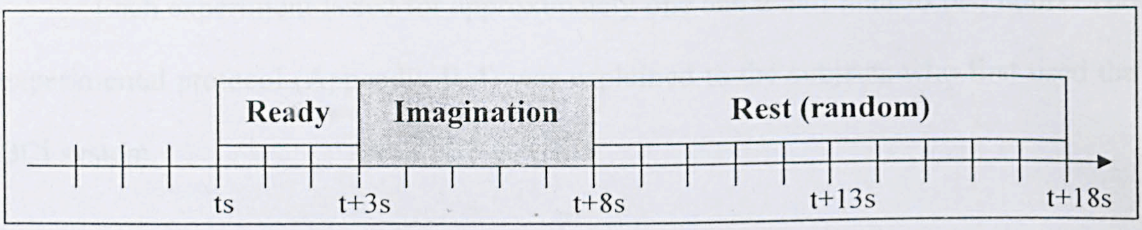


Figure 2.6. The paradigm for one trial.

After each experiment, the subject would be asked:-

- how the subject viewed and performed the task throughout the experiments.
- whether or not the subject felt sleepy or experienced any emotional changes during the experiments.

2.1.3.2 Online Experiments

There were two phases in the experiments that were conducted using the online system. They are the classifier set-up phase and the testing phase and they are described in *Table 2.4*. The testing phase consists of the subject-training phase and the application phase and there will be no update of the classifier within this period of time.

Table 2.4. Description of the classifier set-up phase and the testing phase.

Phase		Descriptions
Classifier set-up Phase		Artifacts rejection algorithm was applied. Only non-contaminated EEG trials were used to set up the classifier. No feedback was provided.
Testing Phase	Subject-training Phase	Artifacts rejection algorithm was applied. The classifier set up was used to classify the EEG trials. The EEG signals were classified and continuous feedback was given only during the time window when the user was prompted by the computer.
	Application Phase	Artifacts rejection algorithm was not applied. Experiments were conducted only on the subjects who could achieve classification error of less than 20% in the subject-training phase. The classifier set up was used to classify the ongoing EEG signals and the subject would decide when to activate the desired control device by using the selection menu in the GUI. The feedback was provided continuously very second.

Each experiment lasted for approximately one and a half hour to two hours. The experimental protocol (Appendix B-4) was explained to the subjects who first used the BCI system.

(A) Classifier Set-Up Phase

The experimental paradigm is similar to the one used in the offline experiments (Section 2.1.3.1) except that only two types of mental tasks were used. The two types of mental tasks and EEG channels were selected based on the data analysis on the subject's EEG trials collected in the offline experiments (Section 2.2.3).

Each session consisted of 40 non-contaminated trials (20 trials for each mental task) that lasted for about 12 minutes or longer. The paradigm for one trial is shown in *Figure 2.6*. Whenever artifacts were detected by the system, the text of "BLINK" or "ARTIFACTS" was displayed to inform the subjects. There were 3 sessions in the classifier set-up phase and the resting interval between two sessions was 5 minutes. It could be shorter or longer if the subject requested.

The GUI used was the same with the one shown in *Figure 2.5*. However, an additional feature was incorporated into the GUI, that is, the cursor would move to the left or to the right according to the command given to the subject. *Table 2.5* shows the moving direction of the cursor that corresponds to different commands when different mental tasks combinations were used. For example, if the subject used RIGHT and FOOT during the online experiments, the cursor would move a step towards the right side every second if the command given was RIGHT. At the 5th second, the cursor would reach the right end of the slider. It would move back to the center position during REST. If the command given was FOOT, the cursor would move to the left.

Table 2.5. The moving direction the cursor that corresponds to different command when different mental tasks combinations were used.

The combination of the mental tasks used in the experiment	Command	Moving direction
RIGHT and LEFT	RIGHT	Right
	LEFT	Left
RIGHT and FOOT	FOOT	Right
	LEFT	Left
LEFT and FOOT	RIGHT	Right
	FOOT	Left

The cursor was designed to move during the classifier set-up phase even though the EEG signals were not classified so that what was presented to the subject visually during both the classifier set-up phase and testing phase remained the same.

Finally, the 120 EEG trials free of artifacts were processed immediately by the computer. LDA weight vector was set up. The theory of LDA is given later in Section 2.3.4. The LDA 10x10 fold cross-validation was used to check the LDA's ability to separate the EEG patterns of the two different mental tasks. The whole process would take less than 2 minutes and the experiment could be immediately continued with the subject-training phase or application phase.

(B) Subject-Training Phase

The subject was trained to control the BCI system in the subject-training phase. The experimental paradigm was similar to the one used in the classifier set-up phase. The number of sessions ranged from 2 to 9. Six sessions were preferable. However, the experiment would end once the subject felt tired or refused to continue. Each session consisted of 20 non-contaminated EEG trials (10 trials for each mental task). The subject would perform a mental task prompted by the computer.

The EEG signals were processed and classified by the LDA set up in the classifier set-up phase once every second. Continuous feedback was used in the present study. The result of each classification was presented to the subject in the form of the cursor movement every second. After each trial, the cursor would move back to its original position (the center position of the slider).

There were 3 experimental stages in this study. The interface and the feedback system used in each experimental stage are different (*Table 2.6*). Further details of the experimental stages are given in *Table B.2* (Appendix B-5). At Stage 1, the USB interface was used to interface the BCI DAQ system and the computer. At Stage 2 and Stage 3, Bluetooth was used. However, the type of interface used should not have any influence on the classification accuracy. Feedback system 1 was used in Stage 1 and Stage 2. Later, Feedback system 2 was introduced in Stage 3 to reduce the classification error.

Table 2.6. The interface and the feedback system used in the 3 different experimental stages.

Experimental stage	Interface System	Feedback System
Stage 1	USB interface	Feedback system 1
Stage 2	Bluetooth	Feedback system 1
Stage 3	Bluetooth	Feedback system 2

The classification rule and how the feedback was presented to the subjects were different in Feedback system 1 and 2. However, the feedback was provided every second in both systems. The characteristics of the feedback system are presented in *Table 2.7*. The main purpose of averaging the classification results over 5 seconds and introducing the threshold (T_{up} and T_{low}) in Feedback system 2 is to reduce the classification error in the system. How the T_{up} and T_{low} were defined is explained in Section 2.3.4.2.

Table 2.7. The characteristics of the two feedback systems used.

	BCI Version 1 (Feedback system 1)	**BCI Version 2 (Feedback system 2)**
Number of classification classes	2 (Correct or incorrect)	3 (Correct, incorrect or ambiguous)
Time required to make a decision	1s	5s
Samples Classification Rule	Rule 1:- Classified as a)Task 1 if $LDA_{output} > 0$ b)Task 2 if $LDA_{output} \leq 0$.	Rule 2:- Classified as a)Task 1 if $LDA_{output} > T_{up}$ b)Task 2 if $LDA_{output} < T_{low}$ c)Ambiguous if $T_{low} \leq LDA_{output} \leq T_{up}$.
Trials Classification Rule	Not Applicable	Classified as a)Task 1 if $mLDA_{output} > T_{up}$ and at least 60% samples were classified as Task 1 b)Task 2 if $mLDA_{output} < T_{low}$ and at least 60% samples were classified as Task 2 c)Ambiguous if the trial was not classified as Task 1 or 2.
Step size of the cursor	Constant step size (It was assumed that all the classifications have equal strength.)	Varying step size (The step size was dependent on the absolute value of LDA_{output}. If the output was ambiguous, the cursor would not move.)
Performance evaluation parameters	a) Classification accuracy: CR_1 (Equation 2.1) b) Classification error: $CE_1=100-CR_1$	a) Classification accuracy: CR_2 (Equation 2.2) b) Percentage of the ambiguous classifications: CR_{ambi} c) Classification error: $CE_2=100-CR_2-CR_{ambi}$

After each session, the performance was evaluated using two different parameters: classification accuracy (the percentage of correct classifications) and the classification error (the percentage of incorrect classifications). In Feedback system 1, every LDA output of the sample, LDA_{output} in the trial was classified as mental task 1 or mental task 2 using Rule 1 explained in *Table 2.7*. The classification accuracy for each session was computed by using the Equation 2.1.

$$\text{Classification accuracy, } CR_1 = \frac{n_c}{N_c} \times 100\ \% \qquad (2.1)$$

where n_c = The number of correctly classified samples

N_c = The total number of samples classified in one session

In Feedback system 2, every LDA output of the sample, LDA_{output} in the trial was classified as mental task 1, mental task 2 or ambiguous using Rule 2. The averaged LDA output of one trial, $mLDA_{output}$ was evaluated every 5 seconds. A trial was classified as mental task 1 or 2 if and only if 60% of the samples in that trial were classified as mental task 1 or 2 and $mLDA_{output}$ was classified as mental task 1 or 2. The classification accuracy of each session was computed using Equation 2.2.

$$\text{Classification accuracy, } CR_2 = \frac{n_s}{N_s} \times 100\ \% \qquad (2.2)$$

where n_s = The number of correctly classified EEG trials

N_s = The total number of EEG trials classified in one session

(C) Application Phase

The BCI Version 2 (with Feedback system 2) was used. Only subjects who could achieve classification error (CE_2) less than 20% in the subject-training phase participated in this study.

Before an experiment, the subject was required to rest for 2 minutes. From the preliminary study, the LDA would be biased to one class when it was used to classify the resting samples, which were different from the two classes of EEG trials used to set up the LDA. If the number of samples classified as mental task 1 in the 2 minutes was two times more than the other class and the averaged LDA_{output} over the 2 minutes was classified as mental task 1, the LDA was considered bias to mental task 1.

The mental task used in the application phase to make a selection was dependent on the LDA bias class as shown in *Table 2.8*. In the worst case, the classifier and the subject had to be retrained if the classification was random and no bias class was identified.

Table 2.8. The mental task used to make a selection in the application phase after a bias class was identified.

Bias Class	Mental task used to make a selection during the application phase
Mental task 1	Mental task 2
Mental task 2	Mental task 1
None	Retrain the subject and classifier

After the bias class was identified, the computer would inform the subject on which mental task to use in making a selection. The mental task is named IM1 and the bias class is named IM2 hereafter in this report. The feedback was provided every second and the cursor would move back to the center position every 5 seconds in the application-based system.

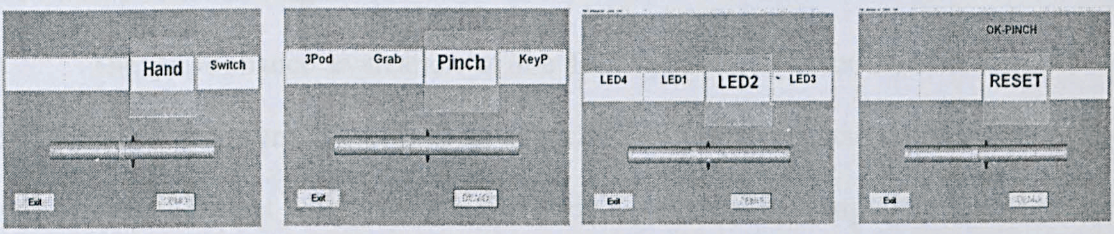
(a) Classification Rules

Each sample was classified by using Rule 2. Each decision was made every 5 seconds. Every 5 seconds, the signals were classified as IM1 or IM2 if and only if 60% of the samples were classified as IM1 or IM2 and $mLDA_{output}$ was classified as IM1 or IM2 using Rule 2. Otherwise, the signals would be classified as ambiguous or incorrect.

(b) Application-Based System Design

The application-based system was used in the application phase. The GUI of the system provides user a selection menu to activate the prosthetic hand and LEDs. There are four different levels in the GUI design: GUI-A [*Figure 2.7(a)*] provides only two options ('Hand' or 'Switch') for the subject to select. If the subject intends to activate the prosthetic hand, the 'Hand' has to be selected to go to the prosthetic hand control GUI (GUI-B1 [*Figure 2.7(b)*]). On the other hand, if the subject intends to activate any LED, the 'Switch' has to be selected to go to the switch control GUI (GUI-B2 [*Figure 2.7(c)*]). Lastly, GUI-C [*Figure 2.7(d)*] is designed for the subject to 'Reset' the prosthetic hand each time after a prosthetic hand movement.

If the subject intends to activate the prosthetic hand or LEDs, the subject has to wait until the desired option appears in the grey box of the GUI and achieve correct classifications of IM1 in 10 seconds (5 seconds to select and 5 seconds to confirm the selection). The confirmation process will reduce the ITR and make the activation of devices more difficult. However, the process can reduce the number of unintended activations of the devices. No confirmation is required to select 'Hand' or Switch' in GUI-A. The selection is simpler so that the subject can more readily go into GUI-B1 or GUI-B2. If it is difficult to select, the subject may be de-motivated.



(a) (b) (c) (d)

Figure 2.7. The 4 GUIs designed for the BCI application-based system.

The activation process of the hand or LEDs in GUI-B1 and GUI-B2 is illustrated in the following example. In this example, IM1 is LEFT and IM2 is RIGHT. During the first 5 seconds:-

- If the signals are classified as RIGHT or Ambiguous, the options will be shifted one step to the right.
- If the signals are classified as LEFT, a selection is made and confirmation is required in the next 5 seconds. In the next 5 seconds:
    - If the signals are classified as RIGHT, the options will be shifted one step to the right.
    - If the signals are classified as Ambiguous, the computer will display the text "Try Harder!" to encourage the subject to concentrate harder and to give a second chance for the subject to confirm the selection. If the subject still fails, the options will be shifted.
    - If the signals are classified as LEFT, the selection will be confirmed.

The descriptions on how the GUI and the system operated are provided in Appendix B-6 and *Figure B.5* summarizes the logic of the BCI application-based system operations.

(c) Experiment Paradigm

The performance evaluation of the BCI application-based system requires an indication of the intent. Therefore, an experimental paradigm was designed in such a way that each subject participated in the study is required to complete a test sequence. In a complete test sequence, the intents of subject are assumed to be the same with the sequence of instructions prompted by the computer. The subject will be prompted to perform 12 device activations and maintain the system in an idle state for 140s. The tasks are summarized as follows:-

- Select 4 different types of prosthetic hand movements (4 device activations)
- Reset the prosthetic hand after every movements (4 device activations)
- Select 4 different LEDs (4 device activations)
- Rest for 20s after one of the prosthetic hand movements was activated.
- Rest for 120s after half of the tasks were performed successfully

The computer will proceed to the next instruction if and only if the subject makes the correct selection as prompted by the computer. The sequence of the selections is preprogrammed and a different sequence is used on the same subject in different experiments. An example of the sequence used is shown in the flow chart in *Figure B.6* (Appendix B-6).

The duration of time used by the subject to complete the test sequence, T_c is compared with the minimum possible time, T_{min} that can be achieved to complete the cycle. T_c is the total of T_s and T_{NA} where T_s is the time when the subject can make a selection and T_{NA} is the time when the subject is not supposed to make a selection. Besides, the number of intended activations (IA), unsuccessful activations (FA), unintended activations (UIA), true positives (TP), false negatives (FN), false positives (FP), information transfer rate (ITR) and Accuracy are calculated. The definition of these parameters is presented in *Table B.3* (Appendix B-6).

T_{NA} is the total time of the waiting time plus the resting period introduced in the sequence. In the design, there may be instances when the subject has to wait for at least 5 to 15 seconds before a selection can be made. For example, the subject is instructed to select 'Hand' followed by '3POD'. After the subject successfully selects the 'Hand', the subject may have to wait for at least 15s before the '3POD' appeared in the grey box and to be selected (as shown in *Figure 2.8*). If any device is activated during this waiting time, 2 FPs and an UIA are generated.

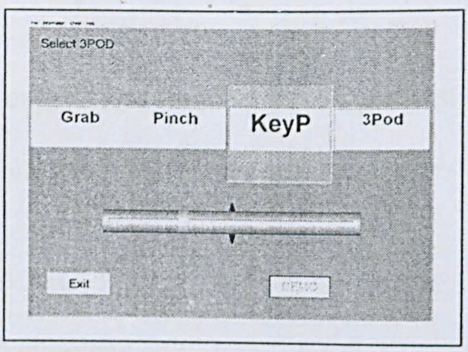


Figure 2.8. GUI-B1: The computer prompts the subject to select 3POD and the subject has to wait for at least 15s before the selection can be made.

Another possibility of a long waiting time is when the subject selects 'Hand' or 'Switch' wrongly and the display becomes GUI-B1 or GUI-B2. The subject will only be able to get back to GUI-A in 2 conditions:-

(a) activate any device

(b) wait for the GUI-B1 or GUI-B2 to terminate after at least 45s

The subject is encouraged to use (b) even though it takes longer than (a) because it will not cause any FP and UIA. On the other hand, action (a) in this test sequence will lead the subject to a penalty of having 2 FPs and 1 UIA.

In a test sequence, there is also a special command 'rest' prompted by the computer. During this resting period, the subject is not allowed to generate any UIA otherwise the subject will never complete the test sequence. The purpose of introducing this resting period is to train the subject to maintain the system in an idle state.

The experiment will be terminated if:

- The subject gives up or the subject feels tired.
- The subject can not complete the cycle in 20 minutes.

In addition to the experiment conducted using a test sequence, each subject is requested to perform the following task after a test sequence:-

a) Rest for 10 minutes
b) Read a book for 10 minutes
c) Solve a mathematical problem

The FP/min and UIA/min are calculated to evaluate the performance of the system when the subject is performing these tasks.

2.2 Data Analysis

Data analysis provides useful information that can be used to:-

1) Assess the discriminating features of the subject.
2) Identify the best two mental tasks and the optimal EEG channels to use during the online experiments.
3) Investigate if the subject has consciously or unconsciously used other artifacts such as EOG or chin EMG signals to control the BCI system.

The two methods used in the data analysis are the R^2 spectral analysis and the LDA 10x10 cross validation.

2.2.1 R^2 Spectral Analysis

The EEG characteristics for each person are different (subject-specific). The coefficients of determination, R^2 can be used in the spectral analysis to find the discriminating features for each subject, assess the EEG control of the subjects and investigate if the subject used non-EEG signals to control the BCI system.

2.2.1.1. Theory of R^2

R is the simple linear coefficient of correlation. The square of R (R^2) is the coefficient of determination. R^2 can be interpreted practically that the straight line model relating y and x can explain (R^2 x 100)% of the variation present in the sample of y values [93]. This concept can be demonstrated in Venn diagram [94] in *Figure 2.9*. Assume that the R^2 value is 0.5. It means 50% of the variation in the EEG signals is accounted for by knowing the cursor's position (or vice versa).

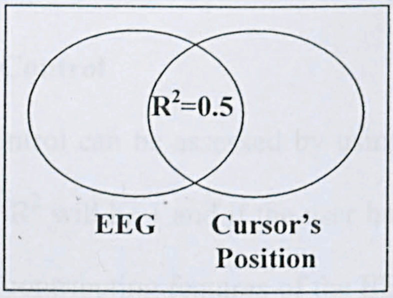


Figure 2.9. Illustration of R^2 using Venn diagram.

Since the R^2 measures the degree of linear relationship between two variables, it can be used to measure the contribution of one variable in predicting the other variable. For example, the contribution of EEG signals in predicting the cursor's position and vice versa can be measured by using R^2.

2.2.1.2. Application of R^2 on the EEG Signals

In the analysis, the AR spectra (order 8) of the raw EEG signals collected in the offline experiments were computed. Next, the cursor's position was assigned the value of 0 and 1 to denote the right and left position (equivalent to the mental task 1 and mental task 2) so that the different positions (different mental tasks) can be identified in the regression analysis. The value of 0 and 1 does not indicate meaningful measurements and it is known as a dummy indicator [95].

The R^2 between the EEG rhythms and the cursor's position is used to measure the user's control of specific EEG features because it serves as a good predictor of system performance [96]. A larger value of R^2 indicates a better user control. R^2 is also used to show that the EEG-based cursor control does not depend on muscle activity [97].

2.2.2 Assess Subject's EEG Control

The subject's EEG control can be assessed by using R^2. If the user has perfect EEG control, the value of the R^2 will be 1 and if the user has no control at all, the value of the R^2 will be 0. The main contributing features of the EEG frequency components in discriminating two mental tasks can be identified from the R^2 spectra.

2.2.3 Identify the Two Mental Tasks and the Optimal EEG Channel(s)

During the offline experiments, EEG trials of the three mental tasks: FOOT, RIGHT and LEFT were recorded using the montage shown in *Figure 2.4*. There are three possible mental tasks combinations that can be used in the BCI system, that is, RIGHT and LEFT, RIGHT and FOOT or LEFT and FOOT. Only one mental tasks combination and one or two EEG bipolar channels derived were identified and used in the online experiments.

In order to identify the combination of the mental tasks and the EEG channel(s), the averaged accuracy of the LDA 10x10 fold cross validation for each mental tasks and the bipolar channels combination was computed. No feature selection algorithm such as GA was used because the possible combinations were not too big. There are nine derived bipolar channels (*Table B.1*, Appendix B-1). Only 36 possible EEG bipolar channel combinations were considered for each mental tasks combination. For example, the Channel ac_C3 (from Region C3) can be used alone or in combination with any other bipolar channels in Region C4 or Region.

In the analysis, the combinations of the EEG channel(s) and the mental tasks that gave the best averaged accuracy obtained from the LDA 10x10 cross validation were selected for each subject and used in the subsequent online experiments (except in the case when a single EEG channel was sufficient to discriminate the two mental tasks, which is discussed in Section 3.1.2).

2.2.4 Check for EOG and EMG Contaminations

Unconscious muscle contractions may contribute to the change in the mu and beta rhythm control of the BCI [97]. It is important to ensure that the subjects involved in the study did not use the non-EEG artifacts generated by the other parts of the body to control the BCI System. Hence, it has to be proven that the EEG activity control used by the subject does not depend on the concurrent EOG and EMG activity.

The relationships between the cursor's position and the power spectra for frequency components (1-60 Hz) of the EEG, EOG and EMG signals recorded during motor imagery were evaluated by using R^2 values. Hypothesis testing was then performed to check if the non-EEG signals are significant in predicting the cursor's position.

2.3 Online Signal Processing and Classification

2.3.1 Artifacts Rejection (Threshold Method)

Artifacts will contaminate the EEG signals. There are a few methods to detect artifacts online. For instances, FFT power spectra were used to detect muscle and ocular artifacts [62] and the threshold method was to detect ocular artifacts [42,79]. In the present study, the threshold method was used because it is effective and easy to implement.

The threshold method was used to define eye-blinks, spikes and artifacts generated by the mouth or jaw in the online experiments. The eye-blinks were detected by using the EOG channel and the jaw movements were detected by using the chin EMG channel. During the classifier set-up phase and subject-training phase of the online experiments, only the clean EEG trials (without eye-blink and jaw artifacts) were used to set-up the LDA and evaluated. However, in the application phase, no artifacts detection method was used because eventually, a more robust classification is desired in practical applications.

In the method, the EEG trials would be rejected if the absolute value of the signal acquired exceeded 1000 unit (35μV) at the EOG and EMG channel. However, the contaminated trials would be saved for data analysis. Trials and errors were used in defining the threshold of 1000 unit (35μV). The mean value of the EOG without eye-blinks is approximately 76.4 unit (2.6μV) with a standard deviation of 79.8 unit (2.8μV). As can be observed from *Figure 2.10*, there will be a peak whenever there is an eye-blink. The absolute value of the peak exceeds 1000 unit (35μV) at every instances. *Figure 2.11* shows the EMG signal when the subject moved his or her jaw and *Figure 2.12* shows a spike that can be detected in all the channels (EEG, EOG or

EMG). The spike may be caused by other types of artifacts or by the amplifier and filter system. All of these artifacts exceed the amplitude of 1000 unit (35μV).

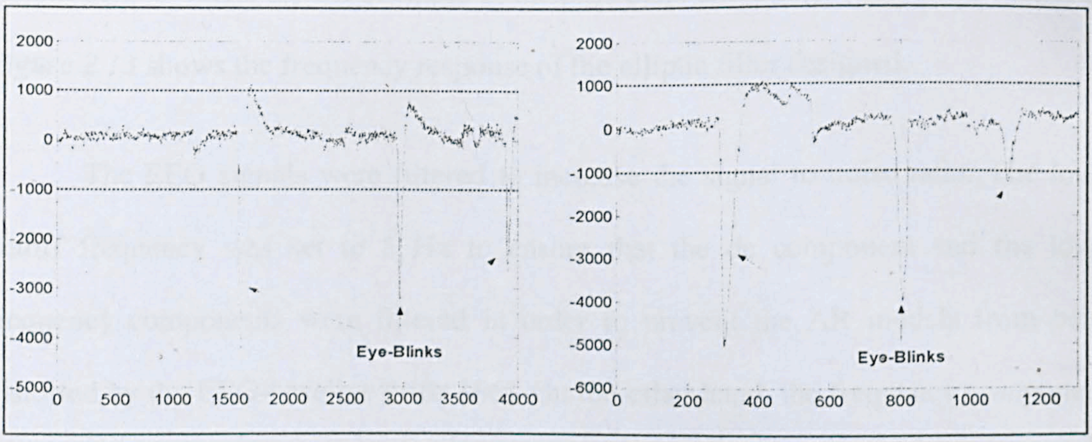


Figure 2.10. EOG signals with eye-blinks.

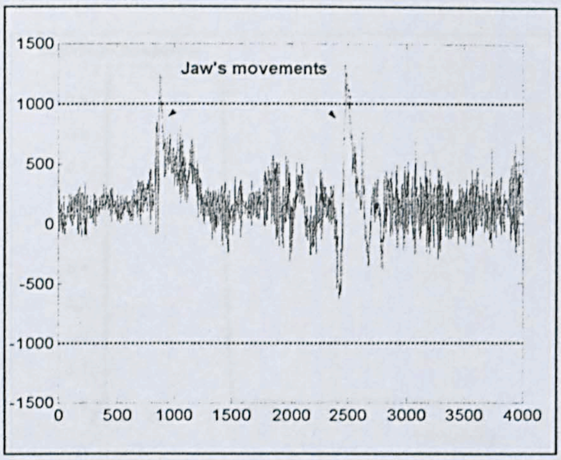


Figure 2.11. EMG signals with jaw movements.

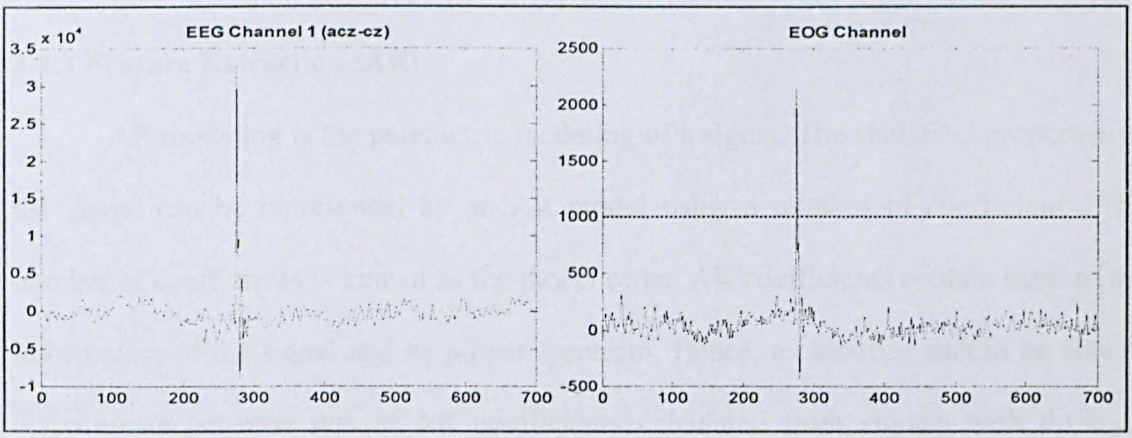


Figure 2.12. A spike detected in the EEG and EOG channels.

2.3.2 Signal Preprocessing (Filter)

The raw EEG signals were band pass filtered using an elliptic IIR filter of order 7 from 5Hz to 40Hz. 0.1 dB of ripple in the pass band and a stop band 40 dB was used. *Figure 2.13* shows the frequency response of the elliptic filter designed.

The EEG signals were filtered to increase the signal to noise ratio. The lower cutoff frequency was set to 5 Hz to ensure that the dc component and the lower frequency components were filtered in order to prevent the AR models from being distorted by the EEG-baseline drifts [66]. On the other hand, the frequency components higher than 40 Hz that were not crucial in the study were also filtered.

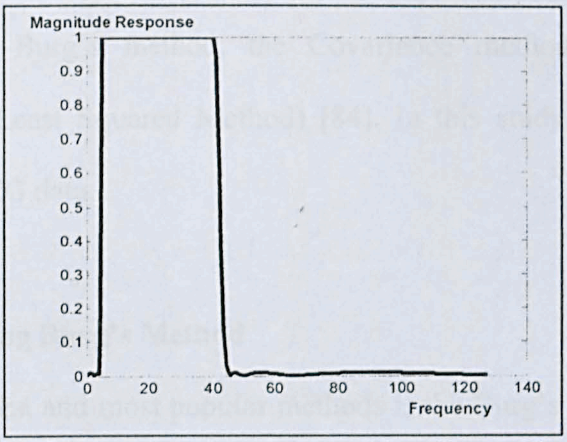


Figure 2.13. The frequency response of the elliptic filter designed.

2.3.3 Feature Extraction (AR)

AR modeling is the parametric modeling of a signal. The statistical properties of the signal can be represented by an AR model using a number of coefficients. The number of coefficients is known as the model order. AR coefficients contain most of the information of the signal and its power spectrum. Hence, a classifier should be able to discriminate between sets of AR coefficients calculated from signals with different spectral properties [72].

In an AR process, the value of a time series at current time period (n) is a linear function of its immediate past value plus white noise (i.e. uncorrelated random variables). It is clearly shown by Equation 2.3.

$$y[n] = \sum_{k=1}^{p} a_k \, y[n-k] + w[n] \qquad (2.3)$$

where $y[n]$:current output

w[n] :white noise with mean zero, variance σ^2

a_k : AR coefficients

p : AR model order

Various methods are available to estimate the AR coefficients, such as the Yule-Walker method, the Burg's method, the Covariance method, and the Modified Covariance method (Least Squared Method) [84]. In this study, Burg's method was used to process the EEG data.

2.3.3.1 Reason of Using Burg's Method

One of the oldest and most popular methods is the Burg's method [98 cited 99]. A comparison of various estimators of AR coefficients showed that the Burg's method is the preferred estimator of AR coefficients [100-102]. Burg's method was selected because it gave better results in EEG analysis over the Kalman filtering and the Yule-Walker method [72].

The Yule Walker method is widely used because it's simple and efficient even though its performance is not as good as Burg's method. However, it can be severely biased [101]. On the other hand, the least-squares estimator and the forward-backward estimator have a greater variance than the Burg's method. The least squares method may yield unstable models [84,101,103].

The major advantages of the Burg's method are summarized as follows:-

- It results in high frequency resolution [3].
- It yields a stable AR model [84,98,103]
- It is computationally efficient [84,98]
- It is an accurate estimator for AR coefficients [104].

2.3.3.2 Burg's Method

In this method, the reflection coefficients are estimated and then used in the Levinson-Durbin algorithm to estimate the AR coefficients. No zero-padding is required as in the Yule-Walker method. The stability of the estimated AR model is guaranteed because the reflection coefficient is always smaller than unity [105].

The Burg's method minimizes the sum of the squared of the forward and backward prediction errors and the reflection coefficients are estimated directly with a recursive algorithm whereby in each recursion step, a single reflection coefficient is estimated. The algorithm of calculating AR coefficients using Burg's method is presented in *Table C.1* (Appendix C-1) [84,106].

The Power Spectral Density (PSD) can be estimated by using Equation 2.4 and the frequency resolution obtained from the AR analysis, res_{AR} can be computed by using Equation 2.5 [106].

$$\mathrm{PSD}(\omega)=\frac{\sigma^2}{2\pi\left|1+\sum_{m=1}^{p}a_m e^{-j\omega m\Delta t}\right|^2} \qquad (2.4)$$

$$res_{AR}=\frac{1.03}{\Delta t.p.[\mathrm{SNR}(p+1)]^{0.31}} \qquad (2.5)$$

where Δt = sampling interval

Equation 2.5 shows that the frequency resolution obtained from the AR analysis can be improved by decreasing the sampling rate or increasing the model order. The resolution does not depend on the number of data point used to estimate the AR coefficients. This is an advantage.

2.3.3.3 Model Order Selection

The model order used to represent the signal in AR is important. Too small of a model will produce a smoothed spectrum and the model will not be able to represent the signal's properties and also cause poor resolution [106]. On the other hand, if the model order is too high (over modeled), the spectrum may contain spurious peaks.

Many approaches have been proposed to select the optimum model order. Among the most commonly used order selection criterion are Akaike's Information Criterion (AIC), Final Prediction Error (FPE), Minimum Description Length (MDL), Parzen's Criterion Autoregressive Transfer Function (CAT) [100]. AIC and FPE are the better known criteria to select the model order and the order is selected by minimizing Equation 2.6 and 2.7.

$$\text{AIC (p)} = \ln \sigma_{wk}^{2} + 2\frac{p}{N} \qquad (2.6)$$

$$\text{FPE (p)} = \sigma_{wp}^{2} \frac{(N+p+1)}{(N-p-1)} \qquad (2.7)$$

The model selection is critical and it needs experience. In this study, 3 approaches were used to select the model order:-

- Consideration of the number of training sets required in setting up a classifier
- AIC selection criterion
- Referring to previous works

(A) Consideration of the Number of Training Sets Required

The sample size requirement is ten times as many as there are independent variables [94]. If the model order used is p, there will be p features extracted from each EEG channel. If two EEG channels are used in the BCI, there will be $2p$ features. Hence, at least $20p$ training sets are required to set up the LDA classifier. During the classifier set-up phase of the online experiments using AR, 300 training sets would be obtained from each mental task. Since the number of training sets available from the classifier set-up phase was small, the AR model order more than 10 were not considered.

(B) AIC Criterion (Equation 2.6)

The EEG signals collected at one of the bipolar channels were segmented into windows (the window size is 1 second, 256 observations). For each window, the signals were filtered and modeled by using Burg's method. The AIC values of AR order from 1 to 10 were computed for each window of filtered signals. The AIC values for each model order were then averaged over windows and presented in *Figure 2.14*.

Statistical analysis ANOVA was then performed on the AIC values. From the AIC ANOVA table (*Table C.2*, Appendix C-2), the hypothesis that the average of the AIC values for all the model order are the same was rejected ($P<0.00001$). By performing Post-Hoc Test using Duncan Test, *Table C.3* (Appendix C-2) was obtained. There are 4 homogeneous subsets. The AIC values for AR model order from 6-10 are shown to be significantly lower than the AIC values for the other AR model order. However, there AIC values for order 6-10 are not significantly different. That means the AR model order 6 is sufficient to represent the EEG signals. Therefore, orders lower than 6 were not considered.

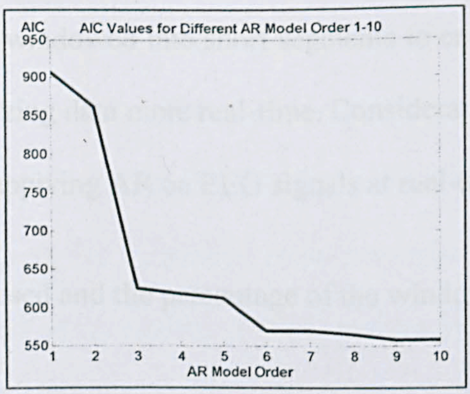


Figure 2.14. AIC values for AR model order ranged from 1 to 10.

(C) Referring to Previous Works

The AR model order commonly used in previous works ranges from 6 to 15 as shown in *Table 2.9*. However, the way of preprocessing the EEG signals by the research groups might be different from the present study. Hence, it can only be used as a reference.

Table 2.9. AR order used by various research groups.

Model order	References
6	[27,34,75,79]
7	[106]
8	[75,80,108]
12	[80,109]
15	[73]

In the present study, AR model order 8 was selected even though the order of 6 was found to be sufficient to represent the signals based on the results of the AIC and the ANOVA. This is because by using a higher order, more details can be incorporated into the model.

2.3.3.4 Application of AR in the BCI System

EEG signals were windowed into short segments to ensure local stationarity and make the process of analyzing data more real-time. Considerations as follows have to be taken into account when applying AR on EEG signals at real-time:-

- The window size used and the percentage of the window-overlap
- Feedback delay

The feedback delay of the system using AR method was one second. Shortening the required time segment to estimate the AR coefficients (window size) can reduce the delay in the feedback provided to the user. Offline analysis comparing window size of one second and half a second showed that the shortening of the segments will affect the accuracy. This is because a more accurate model can be obtained if more data points are used to estimate the model. Hence, the window size of one second was used in this study. There was no overlap between two consecutive windows because it was found that it did not increase the accuracy even though the use of overlapping window increased the number of the training sets.

2.3.4 Classification (LDA)

A classifier separates two or more classes of objects and allocates new observations to one of the classes [113]. The classification rules are usually developed from training samples. The features extracted from each class are examined for differences and divided into two regions, R1 and R2. If a new observation falls in R1, it is allocated to population Class 1, and if it falls in R2, it is allocated to the population Class 2. The classification rules cannot provide an error-free method of assignment because the classes may overlap.

2.3.4.1 Fisher's Linear Discriminant Analysis (LDA)

LDA is used in the present study because it is simple and robust. Besides, it requires smaller training samples to estimate its coefficients [7]. It does not assume that the populations are from multivariate normal distribution [113]. However, the LDA does assume the populations have a common covariance matrix [113]. The assumptions were shown to be fulfilled when applied to EEG signals [38,87]. The sample pooled covariance matrix shown in Equation 2.8 is used.

$$S_{pooled}^{-1} = \frac{(n_1 - 1)S_1 + (n_2 - 1)S_2}{(n_1 + n_2 - 1)} \qquad (2.8)$$

Where S_i = sample covariance of Class i, i=1, 2

n_i = number of observations of Class i, i=1,2

In LDA, the multivariate observations x are transformed to univariate observations y such that y are separated as much as possible. The LDA coefficients can be obtained by maximizing the variance between samples variance and minimizing the variance between populations. The mathematical formula is shown in Equation 2.9 [113].

$$\max_b \frac{(b'(\bar{x}_1 - \bar{x}_2))^2}{b' S_{pooled} b} = (\bar{x}_1 - \bar{x}_2)' S_{pooled}^{-1} (\bar{x}_1 - \bar{x}_2) \qquad (2.9)$$

Where $\bar{x}_i$ = sample mean of Class i, i=1,2

b = LDA coefficients = $(\bar{x}_1 - \bar{x}_2)' S_{pooled}^{-1}$

$$b_0 = \log\left(\frac{n_1}{n_2}\right) - \frac{1}{2}(\bar{x}_1 - \bar{x}_2)' S_{pooled}^{-1} (\bar{x}_1 + \bar{x}_2)$$

The linear function obtained is $\hat{y} = (\bar{x}_1 - \bar{x}_2)' S_{pooled}^{-1} x = bx$. The function will transform an observation, x with p-dimensions to a scalar number, $\hat{y}$. For a new observation x, the classification rule (Rule 1) for Fisher's LDA is as follows:

Allocate x to Class 1 if $b_0 + bx > 0$ OR

Allocate x to Class 2 if $b_0 + bx \leq 0$

The accuracy can be used as a means to measure the classifier's performance, that is, how well the classifier allocates the future samples correctly. The accuracy can be calculated from the confusion matrix table [113] shown in *Table C.4* (Appendix C-3).

2.3.4.2 Determine the Threshold

The threshold was determined immediately after the LDA was set-up and used in subsequent testing phase. Simple statistical method explained in the next paragraph was used to determine the threshold used in the classification because it is simple and can be easily implemented online. Other method such as the Receiver Operating Characteristics (ROC) curves was not considered because the curves have to be produced before a threshold can be determined. This is more difficult to implement online as compared to the statistical method used in the present study. Furthermore, the step size of the feedback cursor can be defined by using the two thresholds determined in the statistical method.

Rule 1 is the sample classification rule used in the BCI Version 1 (Section 2.1.3.2 (B)). In the BCI Version 2, a different sample classification rule (Rule 2) was used. A third class (ambiguous samples) was introduced in the rule to reduce the classification error. *Figure 2.15* illustrates the two different classification rules, that is, Rule 1 and Rule 2. R1 is the region that belongs to Class 1, R2 is the region that belongs to Class 2 and R3 is the region that belongs to the ambiguous samples. T_{up} and T_{low} are the upper and lower thresholds used to define the ambiguous samples.

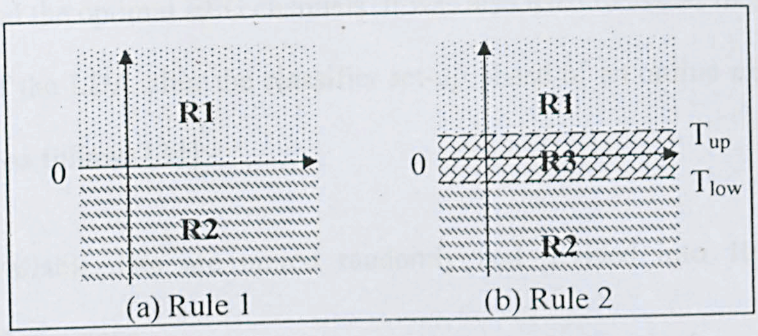


Figure 2.15. Two different classification rules used.

Table 2.10 summarizes the method used to define the thresholds for Rule 2 used in Feedback system 2. The parameters p_1 and p_2 are the proportion of the distance between the quartile and mean of Class 1 and Class 2 respectively. The distance between T_{up} and the mean of Class 1 will be larger than the distance between T_{low} with the mean of Class 2 if p_1 is larger than p_2. In the feedback system 2, the step size of the moving cursor is dependent on the magnitude of LDA_{output} of the EEG signals classified. The step size ranged from 0-4. *Figure C.1* (Appendix C-4) summarizes the conditions in which step size from 0-4 were used.

Table 2.10. Method to define the T_{up} and T_{low} in Rule 2.

Steps
1) Set up the LDA using the training samples collected.
2) Test the LDA by using the training samples.
3) Find the 1st quartile and mean of the training samples' LDA_{output} for Class 1 and Class 2 respectively.
4) Find the absolute value of the distance (s_i) between the mean (μ_i) and the 1st quartile (q_i) for class i=1,2.
5) $T_{up}=\mu_1(1-p_1)$ $T_{low}=\mu_2(1-p_2)$ where $p_1=\dfrac{\lvert s_1\rvert}{\lvert s_1\rvert+\lvert s_2\rvert}$ and $p_2=\dfrac{\lvert s_2\rvert}{\lvert s_1\rvert+\lvert s_2\rvert}$

2.3.4.3 Cross Validation

In this study, a 10x10 fold LDA cross validation was used to identify the best mental tasks and the optimal EEG channels. It was also used to assess the generalization performance of the LDA after the classifier set-up phase of an online experiment. The procedures are as follows [34]:-

1) The available data are mixed randomly and divided into 10 equally-sized disjunct partitions.
2) Each partition is used as the testing sets and the remaining 9 partitions are used as the training sets.
3) Steps 1) to 2) are repeated 10 times to improve the estimate of the accuracy of the LDA. The generalization performance can then be measured by averaging the accuracy obtained when tested on the test partitions of the data for each of the 10x10 LDA models.
4) Hence, 100 averaged values of the estimate are obtained and averaged again.

CHAPTER 3
RESULTS

CHAPTER 3 RESULTS

The data analysis on the EEG signals and the initial results obtained using the BCI system during the online experiments are presented. An overview of the subsections discussed in this chapter is shown in *Figure 3.1*.

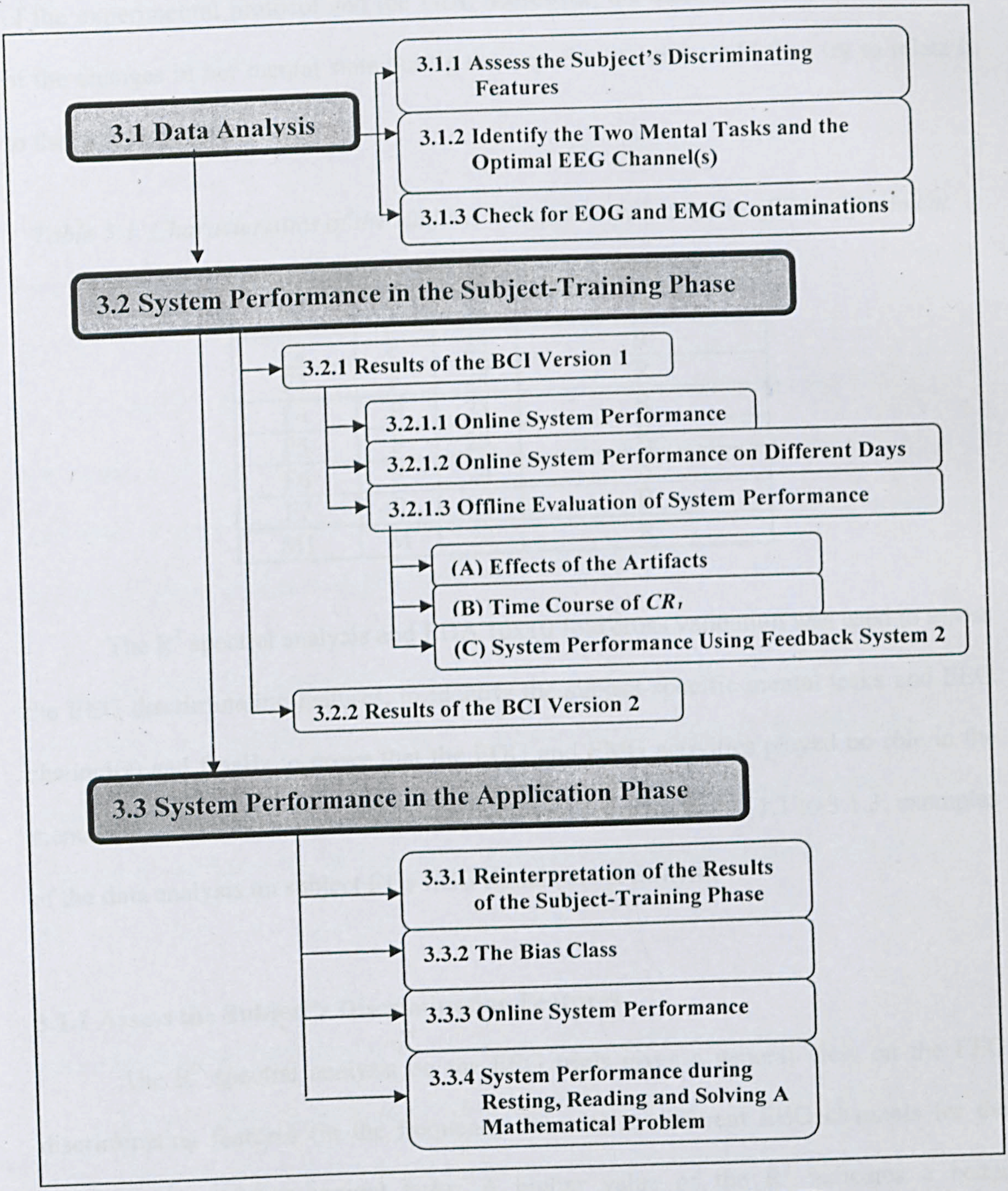


Figure 3.1. The subsections in CHAPTER 3 RESULTS.

3.1 Data Analysis

Eight subjects (7 females [F1-F7] and 1 male [M1]) participated in the offline experiment. The characteristics of the subjects are shown in *Table 3.1*. It has to be noted that the main subject, F1 is the author. The author's experience was useful in the design of the experimental protocol and the GUI. Moreover, the author would be more aware of the changes in her mental state during the experiments and could then try to relate it to the system performance.

Table 3.1. Characteristics of the subjects who participated in the offline experiment.

Subjects	Sex	Age	Dominant Hand
F1	F	24	R
F2	F	25	R
F3	F	24	R
F4	F	23	R
F5	F	23	R
F6	F	24	R
F7	F	24	R
M1	M	22	R

The R^2 spectral analysis and LDA 10x10 fold cross validation was used to assess the EEG discriminating features, to identify the subject-specific mental tasks and EEG channel(s) and finally to prove that the EOG and EMG activities played no role in the mental tasks discrimination or in the BCI control. From Section 3.1.1 to 3.1.3, examples of the data analysis on subject F1's EEG signals are presented.

3.1.1 Assess the Subject's Discriminating Features

The R^2 spectral analysis on the EEG trials gives a general view on the EEG discriminating features (in the frequency domain) at different EEG channels for the discrimination of two mental tasks. A higher value of the R^2 indicates a better discrimination of the two mental tasks and a better subject's EEG control in the online experiments.

An example of the R^2 spectral analysis on subject F1's EEG signals is presented in this section. The R^2 spectra of the 9 bipolar montage for the discrimination of two mental tasks are shown in *Figure D.1* (LEFT vs FOOT), *Figure D.2* (RIGHT vs FOOT) and *Figure D.3* (RIGHT vs LEFT) in Appendix D.

The R^2 spectra showed that the EEG power spectrum centered at 23 Hz in channel ac_CZ or ap_CZ (at the foot representations area) is the main discriminating features between LEFT and FOOT (R^2=0.53 for channel ac_CZ and 0.52 for channel ap_CZ), or RIGHT and FOOT (R^2=0.49 for channel ac_CZ and 0.47 for channel ap_CZ). The R^2 value of 0.53 indicates that 53% of the variations in the EEG signals correspond to LEFT and FOOT is accounted for by the 23 Hz EEG power spectrum. However, no significant discriminating features between RIGHT and LEFT is observed and the R^2 values fall below 0.05 (*Figure D.3*).

The main discriminating features and the R^2 values for each subject are different [97]. Higher accuracies of the LDA 10x10 fold cross validation were observed in the subjects with higher R^2 values. The R^2 spectrum for each subject and the averaged accuracy of the LDA 10x10 fold cross validation is presented in *Table D.6* (Appendix D).

3.1.2 Identify the Two Mental Tasks and the Optimal EEG Channel(s)

The selection of the EEG channels and the mental tasks combination to be used in the online experiments was based on the results of the averaged accuracy of the LDA 10x10 fold cross validation. The results were compared with the results obtained from the R^2 spectral analysis in the previous section. An example on how the two mental tasks and the EEG bipolar channels for subject F1 were selected is presented.

The accuracies of the LDA 10x10 fold cross validation for each of the 36 possible EEG channel(s) combinations were computed for every mental tasks combination. The averaged accuracies are presented in *Table D.1* (Appendix D). From the table, the averaged accuracy for any EEG channel(s) combination using RIGHT and LEFT is less than 65%. The R^2 spectral analysis of subject F1 had already shown that there were no significant discriminating features between these two mental tasks. Therefore, the use of RIGHT and LEFT in the online experiments was not considered. *Table D.1* also shows that ac_CZ and ap_CZ are the optimal EEG channels in both the mental tasks combinations. Similar results were obtained using R^2 spectral analysis.

Next, only the EEG channel(s) combinations with more than 90% accuracy were considered. Therefore, 7 EEG channel(s) combination for the discrimination of LEFT and FOOT and the discrimination of RIGHT and FOOT were selected respectively for further analysis.

For other subjects, 5 to 15 EEG channel(s) combination with the best accuracy were selected and further analysis was performed on the data if and only if one or more of the selected EEG channel(s) combination were single EEG channel. Otherwise, the EEG channels combination with the highest accuracy was selected without further analysis. If the highest averaged accuracy was below 65%, the subject was required to repeat the experiment with other imaginary mental task.

One-way ANOVA was used to further analyze the data. The null hypothesis is that the accuracies obtained by using LDA 10x10 fold cross validation are equal across the 7 bipolar EEG channel(s) combinations. The ANOVA table for LEFT/FOOT and

RIGHT/FOOT are shown in *Table D.2* and *Table D.3*. Both ANOVA table shows that the differences are significant ($F_{0.01,13,1386}$=95.298, P=0.000 for LEFT and FOOT; $F_{0.01,13,1386}$=85.634, P=0.000 for RIGHT and FOOT).

Next, Duncan's test was performed on the data to identify the source of the differences and the homogeneous subsets obtained from the test were shown in *Table D.4* (LEFT and FOOT) and *Table D.5* (RIGHT and FOOT) respectively in Appendix D. In the homogenous subsets, the differences between the means of the constituent groups are not significant.

Table D.4 and *Table D.5* show that the accuracies of the EEG channel(s) combinations using ac_CZ as one of the channel in the classification of LEFT and FOOT or RIGHT and FOOT are significantly higher than those using ap_CZ. In both mental tasks combinations, the accuracies obtained using the EEG channel ac_CZ alone are significantly different from the accuracies using EEG channels of pc_C4 and ac_CZ. However, neither has been shown to be significantly different from the other EEG channels combinations using ac_CZ. Only EEG channel ac_CZ selected for subject F1 because fewer electrodes are used. The mental tasks selected were LEFT and FOOT because the averaged accuracy of for this combination is higher than the RIGHT and FOOT combination.

The discriminating features and the optimal EEG channels are subject-specific. *Table D.6* (Appendix D) presents the R^2 spectra, the discriminating features of each subject with the use of the selected mental tasks and EEG channels for the online experiments, the mental strategy used and the averaged accuracy of the LDA 10x10 fold cross validation.

The distribution of the R^2 spectra patterns and the discriminatory power measured by the R^2 value vary with subjects. *Table D.6* shows that those subjects with higher R^2 values and wider distribution of the discriminating features (larger area under the R^2 spectra curve) achieved higher accuracy. Subject F2 and F7 achieved accuracy lower than 70% and were with low R^2 value. The results for other subjects are more promising.

The mental task combination of LEFT and FOOT was selected in all the subjects. The bipolar channels derived from the electrodes placed at the foot representation area of the sensorimotor cortex (channel ac_CZ, pc_CZ or ap_CZ) are not necessarily the optimal EEG channel in discriminating LEFT and FOOT for some subjects such as subject F4 and F5. For subject F1 and F3, a single EEG channel is sufficient to discriminate LEFT and FOOT.

3.1.3 Check for EOG and EMG Contaminations

It is important to ensure that the EOG and EMG activities played no role in the mental tasks discrimination or in the BCI control. Examples on how the R^2 spectral analysis was used to check for the EOG and EMG contaminations in subject F1's offline and online experiments are presented.

3.1.3.1 Offline Experiments

The mental tasks and the EEG channels selected for subject F1 were LEFT/FOOT and channel ac_CZ respectively. Subject F1 achieved averaged accuracy of 94.06% in the offline experiment. In *Figure D.4* (Appendix D), the R^2 spectrum of channel ac_CZ was compared with the R^2 spectrum of other non-EEG bipolar channels, which include the EOG (*Figure D.4 (a)*), the EMG of the right hand (*Figure D.4 (b)*), the EMG of the left hand (*Figure D.4 (c)*) and the EMG of the chin (*Figure D.4 (d)*).

Figure D.4 shows the main discriminating features focused in the EEG β rhythm (centered at 23 Hz). The maximum EOG or EMG R^2 values at the frequency range of 0-128 Hz fall below 0.02 and are therefore significantly lower than the maximum EEG R^2 value of 0.53 at ac_CZ ($P<0.0001$). This indicates that the EOG and EMG activities recorded during the offline experiment did not contribute to the discrimination of LEFT and FOOT.

3.1.3.2 Online Experiments

The R^2 spectrum of the EEG control channel (ac_CZ) was compared with those of the EOG and EMG (chin) bipolar channels recorded during the online experiments of subject F1. An example of the R^2 spectra obtained from Experiment 1 (Exp1) is shown in *Figure 3.2*. The R^2 values for the EOG and EMG channels are significantly lower than the maximum EEG R^2 value.

The average of the maximum EEG R^2 value over all the online experiments for F1 is 0.2836 (s.d. 0.0289). The EMG R^2 value 0.0102 (s.d. 0.0088) and the EOG R^2 value is 0.0115 (s.d. 0.0133). The values are significantly smaller than the maximum EEG R^2 value ($P<0.00001$). This indicates that the EMG and EOG activities are minimally correlated with the cursor's position when subject F1 was using the EEG signals to control the BCI system.

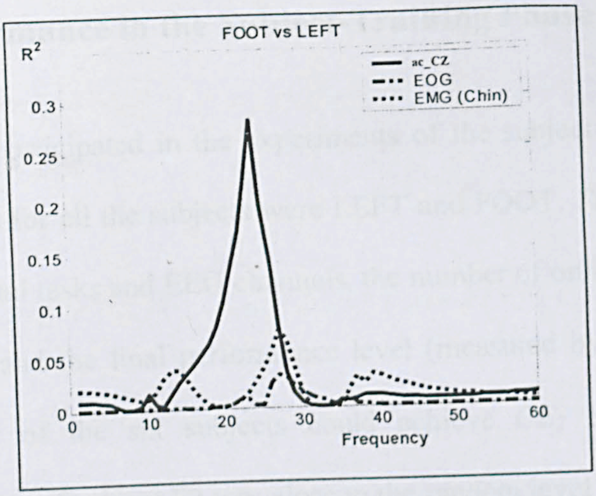


Figure 3.2. The comparison of the R^2 spectrum of ac_CZ, EOG and EMG bipolar channels recorded during online experiment, Exp1.

The same analysis methodology was applied on the other subjects. The maximum EEG R^2 values for F3, F4, F5, F6 and M1 are 0.22, 0.26, 0.26, 0.13 and 0.14 respectively. The EMG R^2 values are low, averaging 0.0345 (s.d. 0.0871) compared to the EEG R^2 values. The EMG and EOG activities are not responsible for the discrimination of LEFT and FOOT in these subjects.

For subject F2 and F7, the EEG R^2 values are low (<0.10). Both their EEG, EOG and EMG activities show little or no discriminating features in the classification of LEFT and FOOT.

3.2 System Performance in the Subject-Training Phase

Six subjects participated in the experiments of the subject-training phase. The selected mental tasks for all the subjects were LEFT and FOOT. *Table 3.2* presents the subject-specific mental tasks and EEG channels, the number of online experiments each subject participated and the final performance level (measured by CR_2 and CE_2) they achieved. Four out of the six subjects could achieve CE_2 less than 20%. The classification accuracy of subject F2 was close to the random level of 50%. Subjects F2, F4 and F5, all of whom participated only once in the experiment, may be able to improve the classification accuracy and error with more training.

Table 3.2. Subject-specific mental tasks and EEG channels, the number of experiment(s) each subject participated and the final performance level they achieved

Subject	Mental Tasks	EEG channels	Number of Experiments	Final Performance level (CR_2/ CE_2%)
*F1	LEFT + FOOT	ac_CZ	10	71.3/0.0
F2	LEFT + FOOT	ac_C4, ac_CZ	1	46.0/40.0
*F3	LEFT + FOOT	ap_CZ	3	61.3/5.0
F4	LEFT + FOOT	ap_C3, ac_C4	1	69.0/23.8
F5	LEFT + FOOT	ac_C3, ac_C4	1	63.3/13.3
*M1	LEFT + FOOT	ac_C4, ac_CZ	4	69.5/4.0

* Subject participated in the application phase of the online experiments.

There are three experimental stages. The number of subjects participated in each stage is different as shown in *Table 3.3*. The details of the three experimental stages are given in *Table B.2* (Appendix B-5). At Stage 3, only three out of the five subjects (subjects with * in *Table 3.2*) participated in the application phase.

Table 3.3. The number of subjects participated in the different experimental stage.

Experimental stage	No of subjects	Subject
Stage 1	1	F1
Stage 2	3	F1,F3,F4
Stage 3	5	F1,F2,F3,F5,M1

3.2.1 Results of the BCI Version 1 (Stage 1 and Stage 2)

3.2.1.1 Online System Performance

The classification rules and the feedback system used in Stage 1 and Stage 2 were the same. The different interface used in Stage 1 and Stage 2 should not have any effect on the system performance in terms of the classification accuracy (CR_I) or the classification error (CE_I). The number of sessions conducted was different in each experiment because the experiment would end once the subject reported fatigue.

The online system performance in the subject-training phase on the non-contaminated EEG trials (with no artifacts detected online) for subjects F1, F3 and F4 is presented in *Table D.7*. The number of the non-contaminated trials of LEFT and FOOT in a session is 10 except in the 3rd session, Exp5 of subject F1 because she was tired and requested to rest. The online accuracy achieved ranged from 55.0% (subject F3, Exp1, Session 4) to 90.0% (subject F1, Exp4, Session 4). The mean accuracy over all subjects and all sessions of the experiments is 75.97% (s.d. 7.90%).

The performance of subject F1 improved with experiments (from 76.2% in Exp1 to 82.3% in Exp5). However, the performance degraded in Exp6 and Exp7. Possible reasons for the degradation are subject F1 was bored, not motivated and under pressure. Subject F1 also commented that she could not imagine as consistently and as focused in Exp6 and Exp7 as compared to the previous experiments.

For subject F3, the online accuracy improved significantly (from 57.8%, s.d. 2.1% in Exp1 to 74.4%, s.d. 4.7% in Exp2). A possible explanation for the unsatisfactory results in Exp1 is that the system was new to subject F3 and she found the feedback distracting. This could change the EEG signals patterns and affect the performance However, in Exp2, she was more familiar with the system and could concentrate even with feedback.

3.2.1.2 Online System Performance on Different Days

A LDA weight vector was set up in the beginning of every experiment. In practice, this is not desirable because the classifier set-up phase takes time. In order to investigate the possibility of using the previous LDA weight vector set-up, subject F1 performed 2 experiments. In the experiments (Exp3a and Exp3b), the LDA set up in Exp3 (conducted on 24, January, 2005) was used. Exp3a was conducted on the same day as Exp4 (just before Exp4). The performance of the system in these two experiments is presented in *Table D.8* (Appendix D).

By comparing the results of Exp3a and Exp4, the new LDA weight vector set-up in Exp4 showed performance improvement (82.8%) compared to the old LDA set-up (76.1%). This is because the new LDA weight vector was set up by using the EEG trials obtained from the subject on the same day.

Overall, the results of these limited experiments are promising because the LDA weight vector set up in Exp3 was still able to perform with the accuracy of 82.5% even about a month later. However, for the rest of the experiments conducted on subject F1, the new LDA weight vector was still set-up in the beginning of each online experiment in the hope that the performance could be further improved when both the subject and the classifier learned mutually [8]. That means, as the subject learned and experienced the possible EEG signals changes, the LDA was also trained to recognize the changes in the EEG signals.

3.2.1.3 Offline Evaluation of System Performance

(A) Effects of the Artifacts

Only the non-contaminated EEG trials were used in the evaluation of the online system performance in the subject-training phase even though the feedback was still provided to the subjects. In the offline analysis, the effect of the artifacts on the system performance was investigated. The number of contaminated trials and the system performance on these contaminated trials for subjects F1, F3 and F4 are shown in *Table D.9* (Appendix D). For subject F1, only Exp5-7 contained contaminated EEG trials. The overall accuracy achieved when both the clean and contaminated EEG trials were included in the classifications is presented in *Table D.10* (Appendix D).

Table D.9 shows that the mean classification accuracy of these 139 contaminated EEG trials is 76.16% s.d. 10.75%). This is not significantly different from the mean online accuracy in the experiments with the 557 non-contaminated EEG trials (71.79%, s.d. 8.39%) by using t-test at the 99% confidence interval (P=0.0103). From *Table D.10*, the mean accuracy is 71.64% (s.d. 8.32%). The results indicate that the system performance did not degrade when the contaminated EEG trials were used in the classification.

From this study on a limited number of contaminated EEG trials, the LDA was shown to be robust towards the artifacts such as eyes-blinks and jaw or mouth movements that could be detected by the system. However, more results were required in the future work to verify it.

In the later part of the analysis, both the contaminated and non-contaminated EEG trials were used because the LDA was eventually allowed to classify both contaminated and non-contaminated EEG signals in the application phase.

(B) Time Course of CR_1

The time courses (5 seconds) of the averaged accuracy of LEFT and FOOT trials, CR_{1ave} were computed to assess the accuracy achieved by the subjects in every second. Examples of the time courses of the CR_{1ave} of LEFT and FOOT trials for subject F1 collected during the Exp 1, Exp 2 and Exp 3 are presented in *Figure 3.3*, *Figure 3.4* and *Figure 3.5* respectively.

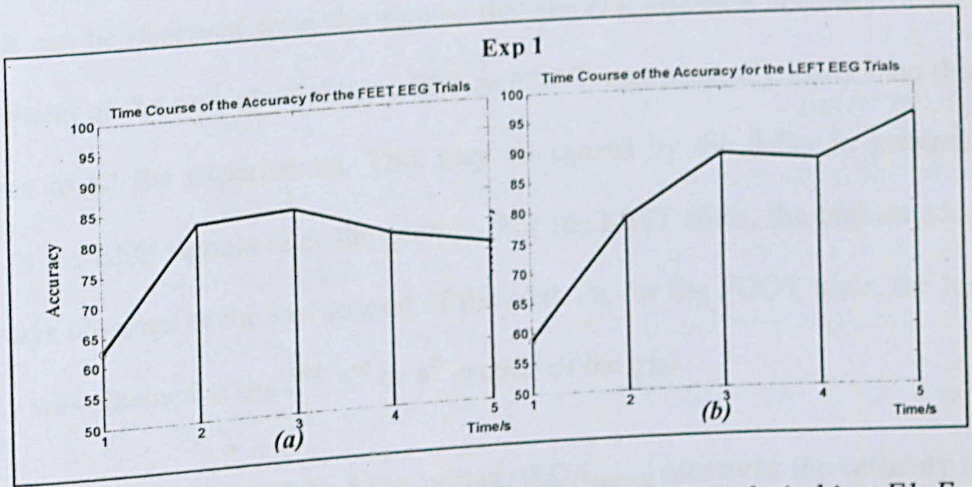


Figure 3.3 Time course of CR_{1ave} for the LEFT and FOOT trials (subject F1, Exp1).

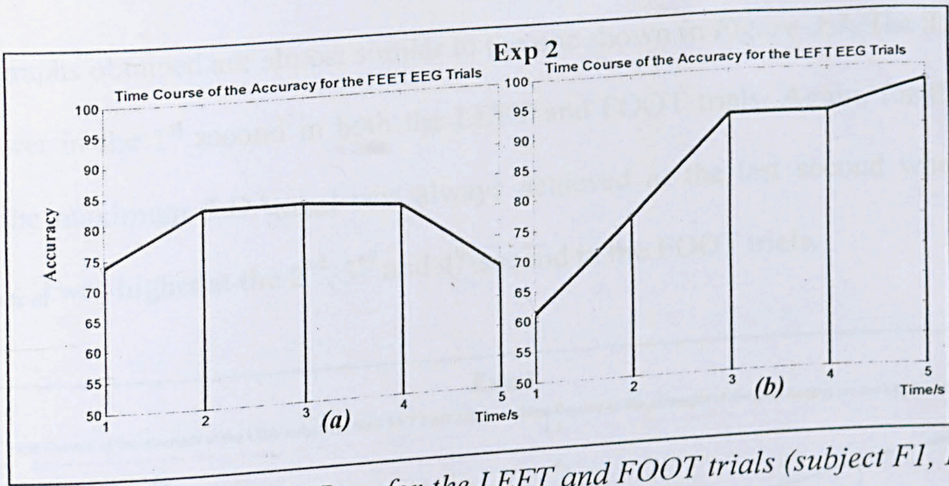


Figure 3.4. Time course of CR_{1ave} for the LEFT and FOOT trials (subject F1, Exp2).

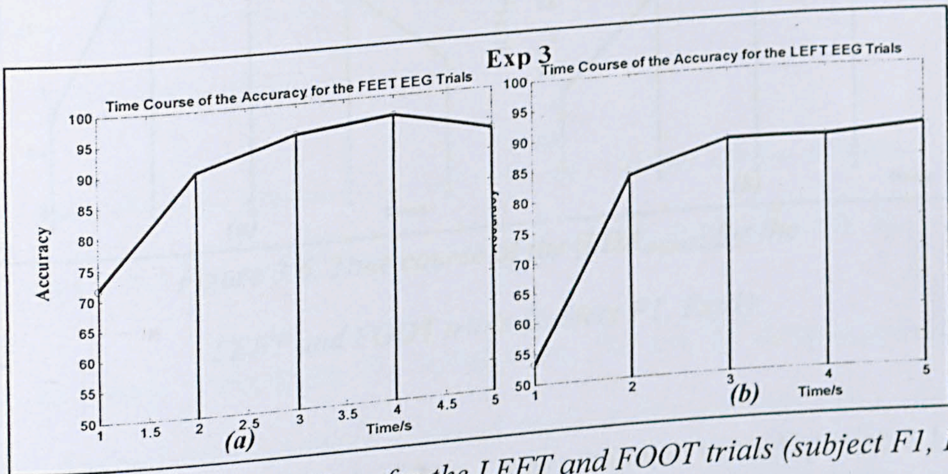


Figure 3.5. Time course of CR_{1ave} for the LEFT and FOOT trials (subject F1, Exp3).

It can be observed from the figures that the classification accuracy of the first time segment of the second of either LEFT or FOOT was generally lower than those at later time in all the experiments. This may be caused by the delay in generating a change in the EEG signals after the prompt. For the LEFT trials, the highest accuracy was always obtained at the last second of the trial. As for the FOOT trials, the highest accuracy was obtained at the 2nd, 3rd or 4th second of the trial

The absolute value of the LDA output, $|LDA_{output}|$ measures the certainty of the classification [34]. The higher the $|LDA_{output}|$, the more correct the classification is. An example of the time course of the $|LDA_{output}|$ averaged across trials for the LEFT and FOOT trials for subject F1 collected during Exp1 were shown in *Figure 3.6*. The trends of the graphs obtained are almost similar to the one shown in *Figure 3.3*. The |LDA_{output}| was lower in the 1st second in both the LEFT and FOOT trials. Again, for the LEFT trials, the maximum |LDA_{output}| was always achieved at the last second whereas the |LDA_{output}| was higher at the 2nd, 3rd and 4th second in the FOOT trials.

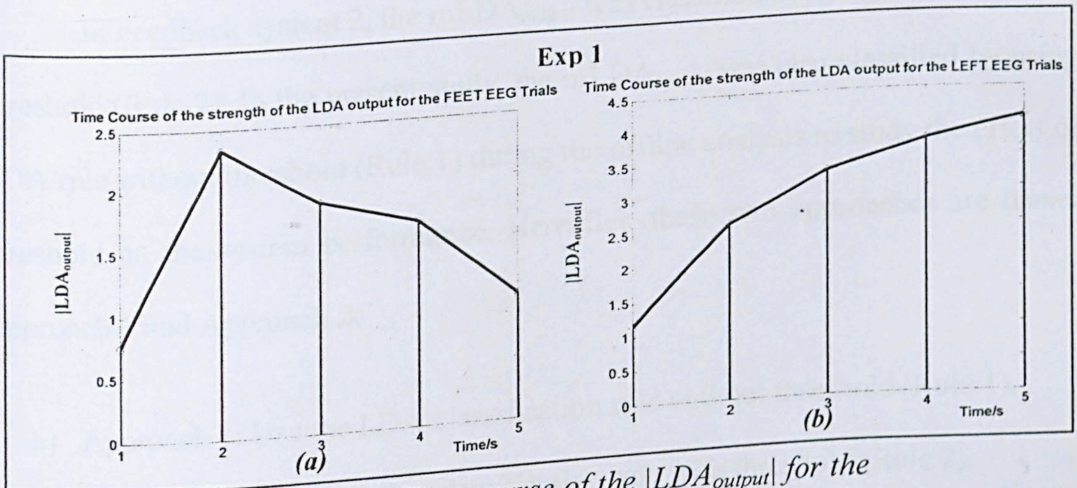


Figure 3.6. Time course of the |LDA_{output}| for the LEFT and FOOT trials (subject F1, Exp1).

Since the CR_1 in Feedback system 1 was computed using Equation 3.1, the low accuracy obtained in the 1st or 2nd second would affect the overall performance in the subject-training phase. The use of averaged classification results over 5 seconds would improve the system performance. On the other hand, the constant feedback step size used in the Feedback system 1 did not provide information on the certitude of the classification results to the subject. The use of a varying feedback's step size was therefore incorporated into the Feedback system 2 so that additional information on the certitude of the classification results was provided to the user. To achieve this, |LDA_{output}| that determined the step size was used. Therefore, the possibility of classifying the EEG signals using the averaged LDA_{output} over the 5 seconds ($mLDA_{output}$) was looked into. In other words, only one decision was made every 5 seconds and the contribution of the sample of each second was weighted by |LDA_{output}|.

It was expected to improve the performance and robustness of the classifier for all the subjects that come at the cost of increasing the duration of time to arrive at a decision.

(C) System Performance Using Feedback System 2

In Feedback system 2, the $mLDA_{output}$ was classified by using the LDA rule with threshold (Rule 2). In the present study, the $mLDA_{output}$ was also classified by using the LDA rule without threshold (Rule 1) during the offline analysis to study the effect of the threshold on the system performance. Hereafter, these two approaches are named as Approach 1 and Approach 2:

a) Approach 1: Use the LDA classification rule without threshold (Rule 1).
b) Approach 2: Use the LDA classification rule with threshold (Rule 2).

The system performance for subjects F1, F3 and F4 using Approach 1 and Approach 2 are presented in *Table D.11* and *Table D.12* respectively (Appendix D). In *Table D.12*, the results are presented in the form of CR_2/ CE_2. The comparison of the classification errors achieved in both approaches is presented in *Table D.13* (Appendix D).

The mean accuracy of Approach 1 and 2 over all the subjects and all the sessions of the experiments are 84.32% (s.d. 12.29%) and 67.37% (s.d. 10.20%) respectively. On the other hand, the mean error of Approach 1 and Approach 2 are 15.68% (s.d. 12.29%) and 5.89% (s.d. 9.18%) respectively. The averaged online classification accuracy and classification error presented in the previous section using Feedback System 1 is 75.97% and 24.03% respectively. Approach 1 significantly improved the classification accuracy and the classification error of the system. The classification error was further reduced by Approach 2.

Real-time feedback was given to the subjects and the EEG signals might be changed by the feedback provided. For example, if the feedbacks were positive, the subject might be motivated; if the feedbacks were negative, the subjects might be depressed. In addition, the approaches used in Feedback system 1 and Feedback system 2 are different. Therefore, a direct comparison between these two Feedback systems is not possible. However, the offline analysis demonstrated the possibility of using the $mLDA_{output}$ and threshold criterion in Approach 2 to reduce the classification error. Therefore, Approach 2 of Feedback system 2 was used in the BCI Version 2. In the system, even though each decision was made at the end of each 5-second trial, the signals were classified and the feedback was provided every second.

3.2.2 Results of the BCI Version 2 (Stage 3)

Table D.14 and *Table D.15* (Appendix D) summarize the online system performance in the subject-training phase obtained using Approach 1 and Approach 2. In several experiments (subject F1, Exp8 & 9; subject F3, Exp3; subject M1, Exp2 & 4), the application phase was conducted immediately after the subject-training phase. Therefore, the number of sessions in the subject-training phase is small (except subject F1, Exp9). Too many sessions may cause fatigue in the subjects and consequently performance degradation in the application phase.

The classification accuracy of subject F2 was close to the random level of 50% and highly biased. The results indicate that she did not have control at all. The classification accuracy achieved ranged from 50.0% (subject F2, Exp1, Session 5) to 100.0% (subject F1, Exp9, Session 2 and 3) in Approach 1 and 35.0% (subject F2, Exp1, Session 4) to 80.0% (subject F1, Exp9, Session 3) in Approach 2. The mean accuracy over all subjects and all sessions of the experiments is 75.82% (s.d. 16.06%) in Approach 1 and 58.63% (s.d.11.32%) in Approach 2.

Table D.16 (Appendix D) compares the classification error of the two approaches. It shows that Approach 2 reduced the classification error significantly. However, Approach 2 may not always reduce the classification error especially in cases when the classification error achieved by using Approach 1 were already low (for example, subject F3, Exp1) or in the case when the classification was random (subject F2, Exp1).

The way to interpret the system performance in the subject-training phase and the application phase is different because only one of the mental tasks (IM1) was used to activate the device in the application-based system. The measures used to evaluate the systems are also different. This is further discussed in the next section where the results are reinterpreted and presented.

3.3 System Performance in the Application Phase

3.3.1 Reinterpretation of the Results of the Subject-Training Phase

Three subjects participated in this study. They achieved classification error of less than 20% (Approach 2) in the subject-training phase. The bias class (IM2) and the mental task used to activate the device (IM1) for all the subjects are LEFT and FOOT respectively. The way to interpret the correct, incorrect and ambiguous classifications in the subject-training and application phase is different as presented in *Table 3.4*.

The results of Approach 1 and Approach 2 shown in *Table D.14* and *Table D.15* are reinterpreted and presented in *Table D.17* and *Table D.18* (Appendix D). *Table D.17* and *Table D.18* show that the error characteristics of Approach 2 are significantly better than Approach 1 with the decrease of 9.93% in P(FP). However, P(TP) was also decreased by 17.62%. In the present application, Approach 2 is a better system in suppressing the UIA since it significantly reduced P(FP). It may be more difficult to make a successful activation. However, it is believed that the activation will become easier as the subjects learn to control the system with further subject training.

Table 3.4. The interpretation of the correct, incorrect and ambiguous classifications in the subject-training phase and the application phase.

	Subject-Training Phase	**Application Phase**
Incorrect classifications in LEFT	CE_2 in LEFT	FP (False Positive)
Incorrect classifications in FOOT	CE_2 in FOOT	FN (False Negative)
Correct classifications in LEFT	CR_2 in LEFT	TN (True Negative)
Correct classifications in FOOT	CR_2 in FOOT	TP (True Positive)
Ambiguous classifications in LEFT	CR_{ambi} in LEFT	TN (True Negative)
Ambiguous classifications in FOOT	CR_{ambi} in FOOT	FN (False Negative)

3.3.2 The Bias Class

Prior to the experiments in the application phase, the subject was requested to rest for 2 minutes to check for the bias class (IM2) and to define the mental task used to activate the devices in the system (IM1). *Table D.19* (Appendix D) presents the results obtained during the 2 minutes resting period for subjects F1, F3 and M1. The total samples being classified is 120. All the subjects shared the same IM1 and IM2.

In addition, in several of the previous experiments using the BCI Version 1, the procedures to check for the bias class was performed on subject F1. The results are presented in *Table D.20* (Appendix D). It was found that, the bias class was always LEFT in the experiments. However, the results do not suggest that the bias class for all the subjects is LEFT in all the mental states other than FOOT. Further studies are required to verify the results and study the system performance in various operating conditions.

3.3.3 Online System Performance

In the application phase, the ongoing EEG activity was classified every second. The subject can self-initiate and use IM1 to activate the devices at any moment even though sometimes the subject may have to wait for a few seconds before the desired option can be selected. The performance of the application-based system was evaluated by using the parameters shown in *Table B.3* (Appendix B-6). The parameters of main concern are the time taken to complete a sequence (T_c), the unintended activations per minute (UIA/min), the information transfer rate (ITR) and the Accuracy.

Test sequence 1 and 2 were tested on the subjects. The optimal values of T_c, T_{NA}, T_S and ITR for the test sequences are shown in *Table 3.5*. The difference in the test sequence was caused by the different waiting time for the desired option to appear in the grey box in each sequence. Therefore, T_c, T_{NA} and ITR varied slightly.

Table 3.5. Optimal values of T_c, T_{NA} and T_S for test sequence 1 and 2.

Parameter	Sequence 1 Optimal value	Sequence2 Optimal value
T_{min}	6m 20s	6m 5s
T_{NA}	3m 40s	3m 25s
T_S	2m 40s	2m 40s
ITR	3 activations/min	3.2 activations/min

Where T_{NA}: The time when the subject is not supposed to make any selection
T_S: The time when the subject is prompted to make a selection

Table D.21 presents the results of each subject during the application phase using test sequence 1 and 2. The same sequence was tested on the subjects twice in 2 occasions: Exp2 (subject M1) and Exp3 (subject F3). All the subjects completed the test sequence even though the ability of each subject to control the system varies. They demonstrated the ability of switch from IM2 to IM1 to activate the prosthetic hand and LEDs, and to maintain the system in an idle state during the resting interval.

For T_c to be shorter than 10 minutes, the ITR and Accuracy had to be more than approximately 1.5 and 85% respectively with the FP/min maintained at low level. The ITR of the subjects ranged from 0.82 activations/min (subject F3, Exp 3a) to 2.06 activations/min (subject F1, Exp8) with the corresponding Accuracy values in the range of 81.38% and 88.74%. In the case of Exp2a and Exp2b of M1, the Accuracies achieved (70.33% and 63.54%) were lower than the Accuracy of 81.38% (subject F3, Exp3a) even though the T_c was shorter and ITR was higher. This is due to the reason that the FP/min of subject F3 is 2.56, which is significantly larger than the FP/min of subject M1 in Exp2a and Exp2b (0.0 and 0.61 respectively).

The penalty of having FP is a longer waiting time for the desired option to appear in the grey box for the subject to make a selection and consequently longer T_c. Even though FP/min may be high (for example 2.56 in Exp3a, subject F3), the UIA is generally lower (<1.0). The UIA/min for the subjects is small (ranged from 0.0 UIA/min to 0.2 UIA/min) except for Exp3a, subject F3 (0.8 UIA/min). The performance of subject F3 was relatively slower (17 minutes with 0.8 UIA/min) in Exp3a because this was the first time that the application-based system was introduced to her and the rules of using the test sequence were explained to her during the experiment.

As for subject M1, there was a slight improvement in the T_c by comparing Exp2b (15m 5s) and Exp4 (9m 15s). However, the performance of Exp2b evaluated by using other parameters degraded. In fact, subject M1 had a very good control in the beginning of Exp2b. He completed half of the test sequence in 2 minutes 50s, and ITR of 2.12 activations/min without any FP. Later, he was tired and had difficulty in performing IM1 to make a selection.

Subject F2, who showed no EEG control in the subject-training phase, was requested to complete the test sequence. She failed to make any activations instructed by the computer even after 18 minutes. If a subject had no control, the classifications would most probably be biased to one class or random. It was not possible to complete the cycle in such conditions since the test sequence not only required the subject to use IM1 to make activations, it also required the subject to maintain the system in an idle state for 140s without making any activations. Therefore, subjects F1, F3 and M1 did not complete the test sequence by chance.

It is more tiring to use the system in the application phase compare to the subject-training phase. This is because the subject has to imagine IM1 for 10 seconds to select and to confirm the selection before a device is activated. From F1's experience, sometimes she had difficulty in imagining IM1 and making a selection before a test sequence ended if she was fatigued. Therefore, when the computer prompted her to select an option, she remained rested before she could imagine IM1 and make a selection again. This may explain why she did not perform any better in Exp9 even though her performance in Exp9 (P(TP)=79.3% and P(FP)=0%) was better than Exp8 (P(TP)=65% and P(FP)=15%).

3.3.4 System Performance during Resting, Reading and Solving A Mathematical Problem

It is interesting to evaluate the system performance when the subjects were performing other activities and were not paying attention to the system. When the subject was requested to read, rest or solve a mathematical problem, he or she did not look at the display. No special command was given to the subjects. The subject was free to move and think. The performance of the system was then evaluated by using the FP/min and UIA/min. The results were presented in *Table 3.6.*

For all the subjects, the results demonstrated that the system was maintained in an idle state when the subjects were resting, reading and solving a multiplication problem in a short period of time. The FP/min is high. As explained earlier (*Table B.3*, Appendix B-6), an UIA is generated from two or three FPs that occur in certain duration of time. Therefore, the application-based system can suppress the UIA/min.

The averaged value of UIA/min is 0.1061 (s.d. 0.1386), which indicates that there may be one or two UIA in 10 minutes time. The initial results are promising in the preliminary studies of the system performance during resting, reading and solving a math problem.

Table 3.6. System performance when the subjects were resting, reading or solving a math problem.

Subject	Bias Class	FP/min (Duration)			UIA/min (T_{NA})		
		Rest	Read	Math	Rest	Read	Math
F3	LEFT	0.900 (10m)	0.333 (10m)	0.766 (3m 55s)	0.100 (10m)	0.100 (10m)	0.255 (3m 55s)
F1	LEFT	0.900 (10m)	0.200 (10m)	1.100 (4m 33s)	0.100 (10m)	0.000 (10m)	0.000 (4m 55s)
M1	LEFT	2.200 (10m)	0.500 (10m)	0.108 (9m 14s)	0.400 (10m)	0.000 (10m)	0.000 (9m14s)

CHAPTER 4
DISCUSSION

CHAPTER 4 DISCUSSION

In this chapter, the findings and the BCI system performance are presented. An overview of the subsections discussed in this chapter is shown in *Figure 4.1*.

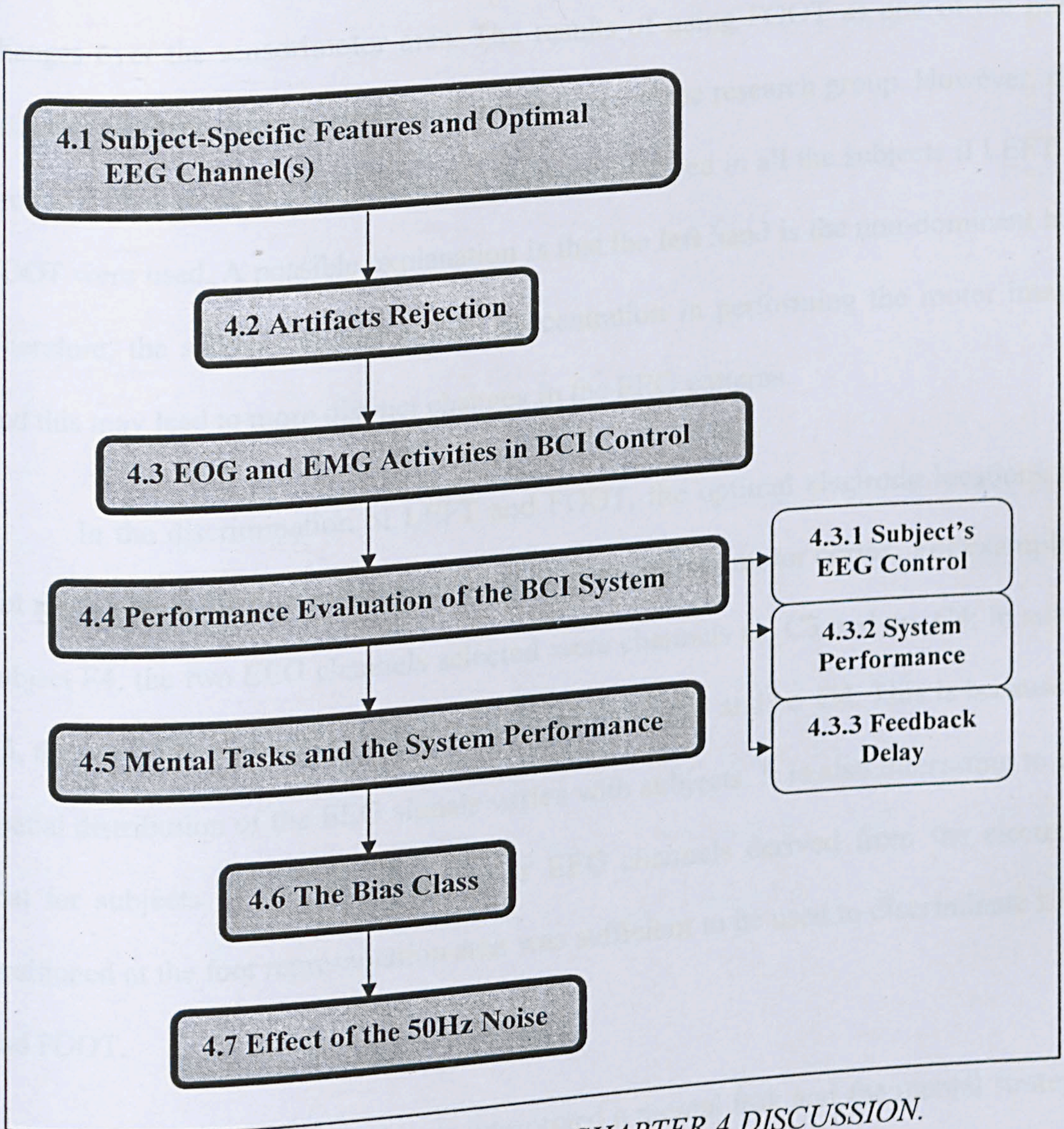


Figure 4.1. The subsections in CHAPTER 4 DISCUSSION.

4.1 Subject-Specific Features and Optimal EEG Channel(s)

Based on the results presented in Section 3.1.1 and 3.1.2, the main discriminating features and the optimal EEG channel(s) are subject-specific. From the results of the offline experiments, the two most distinguishable mental tasks are LEFT and FOOT for all the 8 right-handed subjects. Surprisingly, very minimal discriminating features if at all could be observed in all these subjects from the R^2 spectral analysis for the discrimination of RIGHT and LEFT. In Guger *et al.* [50], all the subjects were asked to perform right-hand versus both-feet imagery in the study because their previous investigations on healthy subjects showed that this would generate distinct EEG changes over the sensorimotor area. The results of using FOOT as one of the mental tasks for all these subjects agree with the findings of the research group. However, more profound changes in the EEG patterns could be observed in all the subjects if LEFT and FOOT were used. A possible explanation is that the left hand is the non-dominant hand. Therefore, the subjects require higher concentration in performing the motor imagery and this may lead to more distinct changes in the EEG patterns.

In the discrimination of LEFT and FOOT, the optimal electrode locations may not always be at the foot representation area of the sensorimotor cortex. For example, in subject F4, the two EEG channels selected were channels ac_C3 and ap_C4; in subject F5, the two EEG channels selected were channels ac_C3 and ac_C4. This is because the spatial distribution of the EEG signals varies with subjects. It is also interesting to note that for subjects F1 and F3, one bipolar EEG channels derived from the electrodes positioned at the foot representation area was sufficient to be used to discriminate LEFT and FOOT.

In addition, how the subjects interpreted a mental task and the mental strategies to use during the experiments vary. Even though the subjects were encouraged to use kinaesthetic imagery, not all the subjects could imagine the feeling. In that case, visual imagery would be used instead. The kinaesthetic imagery was preferable in this study because it was believed to induce more distinct changes in the EEG patterns.

4.2 Artifacts Rejection

In this study, the artifacts rejection algorithm was applied on the EEG signals during the classifier set-up phase and the subject-training phase. Whenever artifact was detected, the computer would inform the subject so that the subject was aware about the generation of the artifacts. Besides, the reliability of the system in detecting the artifacts could be checked.

The artifacts rejection algorithm was applied in the classifier set-up phase of the online experiments so that only the non-contaminated EEG trials were used in the LDA set-up. The artifacts may obscure the EEG activity and may consequently degrade the system performance if the contaminated EEG trials were used to set-up the LDA. This method also ensured that the subject did not use the eyes-blinks and the mouth or jaw artifacts that could be detected by the artifacts algorithm to control the BCI system.

In the subject-training phase, the artifacts algorithm ensured that 20 non-contaminated EEG trials were collected in each session so that the significance and the effects of the artifacts on the EEG data and the classifications could be studied. The computer would still classify and provide feedback to the subject even though artifacts were detected.

In Stage 1 and Stage 2, the system performance in the subject-training phase was evaluated based on the non-contaminated EEG trials only because the robustness of the classifier towards artifacts was still unknown. Later, the offline analysis on the limited number of contaminated EEG trials showed that the system performance did not degrade. Furthermore, the LDA was allowed to classify the contaminated EEG signals in the BCI application-based system eventually, the system performance in Stage 3 was evaluated using both contaminated and non-contaminated EEG signals.

In this study, no artifacts rejection algorithm was incorporated in the application-based system because the rejection of the EEG signals will slow down the device activation process and subsequently the ITR. However, in the future, improved artifacts processing method can be used to isolate or remove the artifacts from the EEG signals instead of discarding the EEG signals with artifacts.

4.3 EOG and EMG Activities in BCI Control

It is possible for the subject to unconsciously use the muscle activities from the other part of the body to control the BCI. Therefore, in the first offline experiment, EOG and EMG channels such as the right hand EMG, left hand EMG and the chin EMG were used to prove that the subject in fact did not use these muscle activities during the experiment to make the mental tasks distinguishable. Only the EOG and the chin EMG channels were used in the online experiments to monitor the non-EEG activity.

From the R^2 spectral analysis on the offline experiment EEG trials, all the subjects who achieved averaged accuracy of LDA 10x10 fold cross validation more than 70% have the maximum EEG R^2 values of more than 0.1 (mean 0.20, s.d. 0.06). The EOG and EMG R^2 values averaged on 0.0345 (s.d. 0.0871) were much lower than the EEG R^2 values. This indicates that discrimination of the two mental tasks did not depend on the EOG and EMG activities. For those subjects who participated in the online experiments, it was also proved that the subjects did not use the EOG and the chin EMG signals in the control of the BCI system.

To further confirm the results, the EOG and EMG signals recorded during the classifier set-up phase of the online experiments were used to set up a LDA weight vector. Next, the LDA was tested on the EOG and EMG signals of the testing phase. As expected, the classification results were at the random level 50%. Furthermore, no evidence of muscle artifacts can be observed from the AR spectra of the EEG signals of these subjects. The results indicate that the EMG and EOG activities had little or no role in the BCI control.

4.4 Performance Evaluation of the BCI System

4.4.1 Subject's EEG Control

In the online experiment, the EEG patterns may change as the subject learns to control the system and tries to adjust the EEG signals so that the classifier can classify it correctly. While concentrating on performing a motor imagery, additional attention is required to observe the feedback and commands. In the application phase, the subject has to decide the appropriate time to make a selection. This may cause the changes in EEG patterns especially in the new subjects. Moreover, the changes in the signals may also be caused by the mental states of the subjects. Some subjects may need more training than others to operate the system.

In Exp3a and Exp3b of subject F1, the feasibility of classifying the EEG signals on different days was demonstrated. It is important to note that subject F1 is an experienced subject and she participated in 10 experiments. She had learned to perform the motor imagery consistently. Therefore, it is possible for her to use the LDA set up from another day. This may not work well for other subjects especially those who are still new in using the system. This could also be explained by the Man-Machine Learning Dilemma (MMLD) suggested by Pfurtscheller and Neuper [8]. As the user learns and experiences the change in EEG patterns, the classifier has to be adapted to the user after one or a few sessions so that the variations of the EEG patterns can be recognized.

For example, the changing distributions of the EEG patterns in subject M1 can be observed by using the R^2 spectral analysis on the data collected during the offline experiment and the online experiment (Exp1 and Exp2) as shown in *Figure 4.2*. In the offline experiment, the main discriminating features were shown to focus in the β rhythm at channel ac_CZ and to a lesser extent in the μ rhythm at channel ac_C4 (*Figure 4.2(a)*). However, in Exp1 and Exp2 (*Figure 4.2(b)* and *(c)*), the difference in the distributions of the EEG patterns can be observed. The subject's EEG control was focused sharply in 10 Hz at ac_C4. The EEG control in the β rhythm at channel ac_CZ becomes weaker and almost insignificant in Exp2. Therefore, the use of the LDA set up in previous experiment would not be appropriate in this case. It will be appropriate only if the subject is trained to generate consistent EEG patterns with more subject trainings.

In this study, all subjects will go through a classifier sep-up phase to set up a LDA before the testing phase so that the LDA could learn the EEG changes in that particular day. Even though subject F1 can use the LDA set up in the previous experiment, she could improve her classification accuracy by using a LDA set up on the same day.

No classifier update is performed during the testing phase. This is because the main objective of the testing phase is toe train the subject to learn to control his or her EEG signals consistently. Subject is advised to be consistent with the mental strategy used during the training phase. Therefore, the classifier will not be updated during the testing phase to confuse the subject.

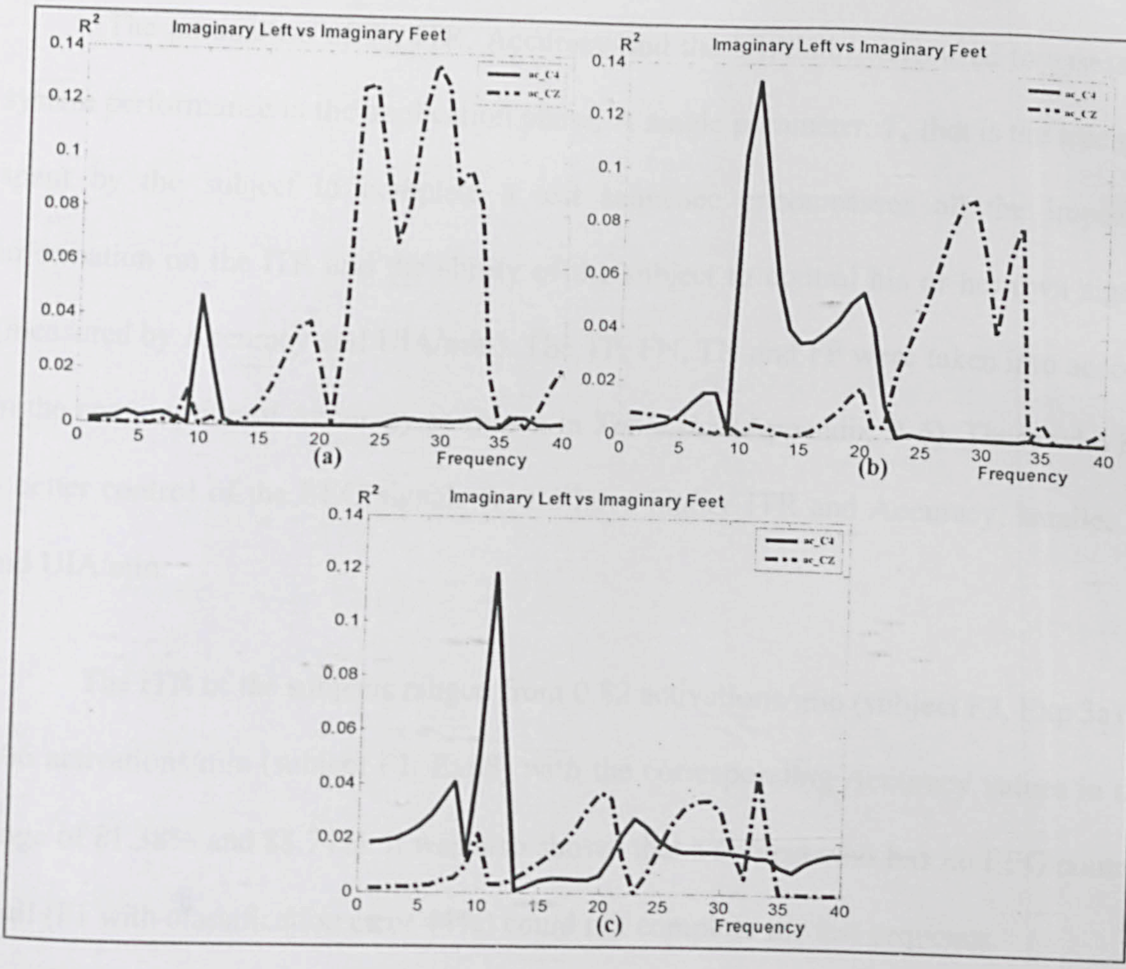


Figure 4.2. R^2 spectra of subject M1 during: (a) Offline experiment; (b) Online experiment, Exp1 and (c) Online experiment, Exp2.

4.4.2 System Performance

All the subjects who participated in the online experiments (except subjects F1 and F4) do not have previous experience in the control of the online BCI system. Four out of the six subjects could achieve CE_2 less than 20%. The classification accuracy of subject F2 was close to the random level of 50%. Subjects F2, F4 and F5, all of whom participated only once in the experiment, may be able to improve the classification accuracy and error with more training.

The parameters of T_c, ITR, Accuracy and the UIA/min were used to assess the system performance in the application phase. A single parameter, T_c that is the true time spent by the subject to complete a test sequence encompasses all the important information on the ITR and the ability of the subject to control his or her own signals (measured by Accuracy and UIA/min). The TP, FN, TN and FP were taken into account in the computation of Accuracy as shown in *Table B.3* (Appendix B-6). Those who had a better control of the EEG signals would have higher ITR and Accuracy, smaller T_c, and UIA/min.

The ITR of the subjects ranged from 0.82 activations/min (subject F3, Exp 3a) to 2.06 activations/min (subject F1, Exp8) with the corresponding Accuracy values in the range of 81.38% and 88.74%. It was also shown that a subject who has no EEG control at all (F1 with classification error 44%) could not complete the test sequence.

The ITR in the application phase is slow, that is, approximately 3 device activations/min if Accuracy is 100%. In our application, the ITR need not be too high because the devices will not be activated as frequently as in the applications of a spelling machine or cursor control. Low FP/min and UIA/min is more critical and desirable. The FP and UIA in the BCI applications will cause inconvenience and problems to the user. If for example, the user is using the prosthetic hand to hold a cup of water. Any UIA at that moment may cause the prosthetic hand to reset and release the cup.

In the present system development, the main focus is on minimizing the FP/min and UIA/min. This could be achieved at the cost of lower P(TP) and ITR. In order to suppress the FP and UIA in the system, Feedback system 2 (Approach 2) that makes a decision once every 5 seconds and with thresholds introduced in the classification rule was used. The subject may have to concentrate harder and take a longer time to make any device activation. This limitation will be overcome when the subject has enough training and a better EEG control. The subject will then be able to constantly generate the EEG signals that are strong enough to activate the device.

However, higher ITR will enable the user to activate the device in a shorter time. It can be improved by reducing the time required to make an activation. The length of time required to make an intended activation, T_{act} in the present system is 10 seconds, that is, 5 seconds to select the desired option and the next 5 seconds to confirm the selection. The trade-off between T_{act} and the Accuracy has to be considered though. If the subject uses a shorter T_{act}, the FP/min may increase. In fact, each subject may have a different optimum T_{act}. Certain subjects may be able to use a shorter T_{act} to activate the device without any increase in the FP/min or UIA/min. Therefore, in future studies, this aspect can be looked into.

In this system, only two types of motor imagery were used in the classification. This poses a limitation on the design of the GUI. The subject had to wait for the desired option to appear in the grey box before a selection could be made. Consequently, the ITR was also reduced due to the waiting time. In future studies, a third class of mental task can be introduced so that a more efficient GUI that improves the ITR can be designed.

More experiments have to be conducted to confirm that the successful performance results of the three subjects in the control of the BCI system hold true for more subjects.

4.4.3 Feedback Delay

Two types of feedback are used by the BCI groups: continuous feedback and discreet delayed feedback. In the continuous feedback, the feedback is provided continuously whereas in the discreet delayed feedback, the feedback will only be presented after a testing trial.

In the present study, the continuous feedback is used so that the subject is conscious about his or her performance continuously when he or she is performing a mental task. The feedback update rate used is once every second. In other words, the feedback delay is 1 second. Indeed, the feedback update rate of once every second is lower than the feedback update rate used by the other research groups as shown in *Table A.3* (Appendix A). According to McFarland *et al.* [45], the delayed feedback may degrade the system performance. The delayed feedback may also confuse the subject. The feedback update rate can be increased by shortening the required time segment to estimate the AR coefficients or by using adaptive signal processing algorithm such as AAR.

In the initial development of the BCI system, the emphasis is on improving the robustness of the system. The shortening of the segments to estimate AR coefficients will affect the accuracy and the AAR is very sensitive towards artifacts [61]. By using AR and the update rate of once every second, the system will be less susceptible towards noise and will reduce the number of FP/min and UIA/min. Furthermore, a faster update rate may not be useful to all the subjects. For the subjects who are still new in the BCI control, it may be better for them to use a system that does not update too frequently. If the update rate is too high, certain subjects who have a slower response may not be able to learn and gain benefits from the high update rate. After the subjects have gained EEG control, a faster update rate would then be more useful.

4.5 Mental State and the System Performance

The mental state of the subject is also one of the important determining factors in the success of the control of the BCI system. Performing the mental tasks in a relax state with high concentration and consistency during the experiment are believed to be important in the EEG control. During the experiments, there might be instances when the subject lose concentration and was distracted by the noise. Many subjects also commented that they became restless and sleepy at the later stage of the experiment. These may be possible reasons for the lower online accuracy achieved by several of the subjects such as subjects F4 and F5. In addition, no motivation such as monetary rewards was given to the subjects.

From personal communication with the subjects and the author's personal experience, the system performance is very sensitive towards the change of the brain states due to the emotional changes. For examples, there were instances when subject F1 was annoyed due to the noise that was distracting her or when she was nervous and under pressure when someone was observing her during the experiment. The classifier was observed to be biased to one class and her performance degraded drastically. Subject F3 also had the same experience because she would lose control whenever she was restless. She would regain her control only when she calmed herself down and remained in a relax state.

These factors may pose a problem in the implementation of the existing BCI system in practical applications because human's brain state changes all the time. There is therefore a need to investigate what type of mental training will enable the subjects to control their brain signals to improve the performance of the BCI system.

4.6 The Bias Class

There is a control class (IM1) and a bias class (IM2) in the BCI application-based system. Whenever a device activation is desired, the subject will use IM1. In real-world applications, it is important for the subject to maintain the bias class when the activation of any device was not desired. It was observed in this study that when the brain states other than the two motor imagery tasks (LEFT and FOOT) used in the BCI system (such as the resting state) were classified, most samples would be classified as IM2. Therefore, in the design of the application-based system, it was assumed that the classifier could identify IM1 (FOOT) from other mental tasks or mental states IM2 (LEFT, REST and e.t.c.).

It is interesting that all the subjects participated in the experiments of application phase shared the same IM1, that is, FOOT when the two mental tasks used were LEFT and FOOT. To investigate this phenomenon, R^2 spectral analysis was performed on subject F1's EEG signals collected during offline experiment. The R^2 spectra for the mental task combination of LEFT vs FOOT, REST vs FOOT and LEFT vs REST are presented in *Figure 4.3*. REST was the EEG data collected during the inter-session resting period. From the figure, there are no significant discriminating features between REST and LEFT. In contrast, the discriminating features in LEFT vs FOOT and REST vs FOOT are similar with the R^2 values are relatively higher in LEFT vs FOOT. In other words, the classifier will not be able to discriminate REST and LEFT. The key to control the BCI in this subject is the FOOT. The same phenomenon was observed in subject F3's and subject M1's EEG data. Perhaps this is the possible explanation why the bias class in subject F1, F3 and M1 is LEFT.

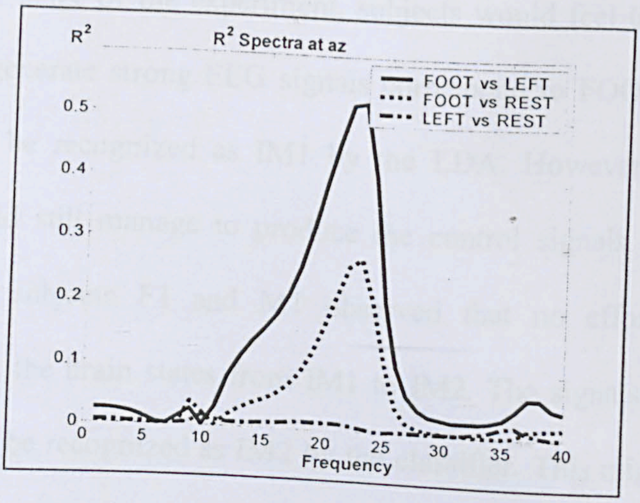


Figure 4.3. The R^2 spectra for LEFT vs FOOT, REST vs FOOT and REST vs FOOT.

Due to this feature, the subjects later found that they did not have to perform LEFT in order to maintain the bias class. Instead, they would just rest and relax.

LEFT will then appear to be useless in the application phase. In fact, this may not be true. For certain subjects, the EEG signals may take longer time to change from one state to another. For subjects F1 and M1, LEFT was useful in speeding up the change of brain states from IM1 to IM2. LEFT was also a way to divert the subject F1's attention from the feet because in many instances, the subject would consciously imagine the feelings of feet movement even though she did not intend to do so.

In the beginning of the application phase when the subjects were still fresh, the subjects could usually imagine FOOT easily and a certain time span was needed for the EEG signals correspond to FOOT to vanish. If the time span was too long, it may cause FP and consequently UIA to occur. In order to prevent this from happening, the subject had to consciously change the EEG signals from IM1 back to IM2 by using LEFT. Once the feedback showed that IM2 was achieved, the subject would then relax. From subjects F1's and F3's experiences, relaxation was the key to maintain the system in an idle state.

At the later stage of the experiment, subjects would feel tired and it would be more difficult to generate strong EEG signals correspond to FOOT that could exceed the threshold and be recognized as IM1 by the LDA. However, if they tried hard enough, they would still manage to produce the control signals. After they stopped imagining FOOT, subjects F1 and M1 observed that no effort was required to consciously change the brain states from IM1 to IM2. The signals in the next second would immediately be recognized as IM2 by the classifier. This might indicate that the subject was fatigue.

A short testing session was also conducted on subjects F1, F3 and M1 respectively after the application phase to investigate the system performance when the subject was performing other task and not paying attention to the GUI. Again, the system was maintained in an idle state when they were reading, resting and solving a multiplication problem. There may be UIA within this period. The averaged value of UIA/min is approximately 0.1. Although the result is encouraging, it is still not good enough for real-world applications. Improved signal-processing algorithms are required to reduce the UIA/min. Further investigations on the system performance in other operating conditions and mental states are required. Additional testing is also required to investigate the consistency of the mental task that will be used as the bias class in the application-based environment.

4.7 Effect of the 50 Hz Noise

An interesting phenomenon was observed in F1's EEG signals in several of the online experiments. The R^2 spectra for the training and testing trials collected from Exp1 to Exp5 are shown in *Figure D.5* (Appendix D). The online accuracy, CR_1 for each experiment is also presented in the figure. As expected, the EEG control sharply focused in the β rhythm. However, it is surprising to find that the R^2 values of the frequency band from 35-80 Hz exceed 0.1 in Exp 4 (classifier set-up phase) and higher in Exp5 (classifier set-up phase and subject-training phase) even though the signals was band-pass filtered from 5 to 40Hz. This phenomenon sometimes only happened in the training EEG trials (Exp 1 and Exp4) or testing EEG trials (Exp 2). The occurrence of this phenomenon did not improve or degrade the performance of the system. In Exp 3, Exp3a and Exp3b, the online accuracy achieved was 81.9%, 76.1% and 82.5% respectively even without the occurrence of the phenomenon.

Initially it was suspected to be the artifacts caused by the subject's unconscious muscle activities. However, from the AR spectra, no evidence of the muscle artifacts was observed. The R^2 spectral analysis on the EOG and EMG channel also indicated that the EOG and EMG activities played no role in the BCI control. *Figure D.6(a)* and *(b)* (Appendix D) show the AR spectra for the raw EEG signals of Exp3 and Exp5 respectively. It should be noted that Exp3 is the experiment without the phenomenon and Exp 5 is the experiment with the phenomenon. There is no observable difference in the AR spectra for Exp3 and Exp5 except the small peak at 50Hz (caused by the 50 Hz power line noise) in *Figure D.6(b)*. ERS can be observed in the β rhythm in all the AR spectra.

Figure D.6(c) and *(d)* show the enlarged AR spectra of the two experiments at the frequency range of 40 to 80Hz. In Exp5, the 50 Hz in LEFT is relatively higher than the 50 Hz in FOOT. The difference in the power at 50Hz in Exp3 is not significant if compared to Exp5. Therefore, it was concluded that the high R^2 values of the 35-85 Hz frequency band was caused by the 50 Hz noise.

The next question is why was there a difference in the power of 50 Hz and the frequencies in adjacent to 50 Hz in LEFT and FOOT trials? The reason is that in some experiments, even though the computer randomized the LEFT and FOOT trials, it was possible that most of the FOOT trials were performed in the early session and the LEFT trials were performed in the late session. The 50 Hz noise in the system would increase as time goes by due to the degradation in the electrodes impedance. Hence, the R^2 spectral analysis that considers the ensemble average of the EEG trials showed discriminating features in 35-85 Hz.

It is important to note that the phenomenon does not improve the system performance and the system could still perform with high online accuracy in the experiments without the occurrence of this phenomenon (82.5% in Exp3b). Therefore, the main EEG control of subject F1 is still focused in the β rhythm at channel ac_CZ.

CHAPTER 5
CONCLUSION

CHAPTER 5 CONCLUSION

The newly set-up BCI system was used as an experimental system to control a prosthetic hand and 4 LEDs representing 4 different remote devices. Real-time signal processing and classification algorithms were implemented and a GUI was designed to provide feedbacks and selection menu to the users. The main focus of the present study is to implement a system that is robust and with no unintended activation of the control devices.

The studies demonstrated the feasibility of using AR and LDA to process and classify the two classes of EEG signals that correspond to motor imagery in real-time. Although only three subjects participated in the application phase, the results are promising and indicate that the subjects can learn to use an EEG-based BCI system to control devices such as prosthetic hand. The subjects were also able to maintain the system in an idle state with low UIA when they were resting, reading and solving a mathematical problem.

The ITR is relatively low (ranged from 0.82 activations/min to 2.06 activations/min). However, the UIA/min (mean=0.1) for the above-mentioned three subjects is encouraging. In our application, the ITR need not be too high because the devices will not be activated as frequently as the other applications such as a spelling machine or to control a cursor. Low UIA is more critical and desirable.

The processing of the EEG signals is complicated because the EEG signals are stochastic and noisy. Furthermore, there are inter-trial and intra-trial variability. The characteristics, discriminating features, optimal electrode locations and the best mental strategy are highly subject-specific. The performance of the system is also sensitive to the changes in the mental state of the subjects. Therefore, there is a need to investigate the type of mental training that will help the subjects to improve their EEG control and consequently improve the system performance.

To date, this study has been conducted on healthy individuals. Whether it is possible for the individuals with motor disability to use the motor imagery to control the BCI system remains to be explored.

Here are some suggestions for the future work:-

I) Investigate the possibility of using 3 classes of EEG signals to control the BCI system so that the desired selection can be activated in a shorter time and consequently increase the system information transfer rate.

II) Improved the signal processing and classification methods so that the number of FA/min and UIA/min can further be reduced.

III) Use related algorithms to find the subject-specific optimal time to make an activation without increasing the FP/min.

IV) Explore the effect of the use of a shorter feedback delay by using signal processing algorithms such as AAR.

APPENDIX

APPENDIX A: Reviews and Comparisons of the Existing BCIs

Table A.1. BCI types.

Electrodes Placement	Invasive/ Non-invasive	Type of input brain signals	Asynchronous/ Synchronous	BCI Group [References]
On the scalp	Non-invasive	**EPs**		
		Steady-state Visual Evoked Potentials (SSVEP)	Synchronous	SSVEP China [12-13], SSVEP Air Force Research Lab [14-15]
		P300	Synchronous	P300-based BCI [16-17]
		Spontaneous EEG Signals		
		Slow Cortical Potentials(SCPs)	Synchronous	Thought Translator Device (TTD) [18-19]
		Operant-Conditioning of μ and β rhythm	Synchronous	EEG-based Neuroprosthesis [20], Wadsworth BCI [6,21]
		Event-related EEG patterns	Asynchronous	Graz-BCI [9], Low Frequency-Asynchronous Device (LF-ASD) [22], Adaptive Brain-Interface (ABI) [23]
			Synchronous	Graz-BCI [7,24], Berlin Brain-Computer Interface (BBCI) [25], [26] and [27]
Just Below the skull	Invasive	**EPs**		
		Visual Evoked Potentials (VEP)	Synchronous	Brain Response Interface (BRI) [28]
On the brain surface (Electrocorticogram (ECoG))	Invasive	**Spontaneous EEG Signals**		
		Movement-related Potentials	Synchronous	[29]
Immediately outside neurons (Neuronal Action Potential)	Invasive	**Spontaneous EEG Signals**		
		Movement-related Potentials	Asynchronous	[30], [31] and [32]
		Operant Conditioning of neural signals	Synchronous	[33]

Table A.2. Comparison of the characteristics and performances of various BCIs.

BCI Group	Freq (Hz)	S/R	FBUR	$N_{selection}$	T_{train}	ITR	CR (%)	Ref.
EPs-based BCIs								
BRI	NS	NS	NS	64	10-60m	10-12 w/m	90	[28]
SSVEP Training (Air Force Research Lab)	13.25	1124	NS	2	3-5 1-hour sess	10.6 b/m	96	[14]
SSVEP (Air Force Research Lab)	23.42/ 17.56	1124	NS	2	mins	17.1 b/m	92	[14]
SSVEP (China)	6-14	200	NS	12	3 min	27.15 b/m	31.25-100	[12,13]
P 300	0.01-100	200	NS	36	2 Sess (mins)	2.3 w/m (12 b/m)	95	[16]
Spontaneous EEG-based BCIs								
New Graz-BCI	0.5-30	128	4	2	2-3.5 hours	5-17 b/m	80-97	[34,35]
Wadsworth BCI	8-12/ 20-24	128	10	2	15-20 sess	2-25 b/m	95	[6,36,37]
BBCI	0.05-	1000 (ds100)	23	2	NS	40 b/m	>96	[25,38]
TTD	0.01-40 (<8Hz)	256	16	2	Several months to years	0.5 l/m	70-80	[39,40]
LF-ASD	1-4	128 (ds64)	16	2	1.5-2 hours	NS	>94% TP: 60-81 FP 1.6-6	[22,41,42]
ABI	8-30	128	16	3	A few days-few weeks	2.7 l/m	TP: 70 FP: 5	[23,34]
Asynchronous Graz BCI	10-12 16-24	128	10	3	2 hours	1.99 l/m	>90	[9]
EEG-based neuroprosthesis	25-28	NS	NS	2	6 months (10-20 sess)	8.1b/m	>90	[20]

Abbreviations used:-

Freq: frequency range of the EEG signals; S/R: system sampling rate; FBUR: feedback update rate; $N_{selection}$: number of selections; T_{train}: length of training time; CR: accuracy; ITR: information transfer rate; Ref: References; NS: not stated; ds: downsampling used; sess: sessions; TP: true positive; FP: false positive; b/m: bits/min; w/m: words/min; l/m: letters/min.

Table A.3. The montage and the methods used by various BCI groups in signal preprocessing, feature extraction and classification of the EEG signals.

Research Group [References]	Montage	Signal Preprocessing	Signal Processing	Classification
Synchronous BCI System				
Synchronous Graz-BCI System [7,8,34,62-65]	2 bipolar channels over the cortical hand and foot area	1) Spatial filtering - Common Average Reference (CAR) - Laplace filter - Local Average Technique (LAT) 2) Frequency filtering	1)Band-power 2) Adaptive Autoregressive Model (AAR) 3) Common spatial filter (CSP) 4) Hjorth transformation 5) AR models Feature selection : 1) Distinction Sensitive Learning Vector Quantization (DSLVQ)	1) LDA 2) Hidden Markov Model (HMM) 3) Learning Vector Quantization (LVQ) 4) Artificial Neural Network (ANN) 5) Adaptive Quadratic Discriminant Analysis
TTD [10,18,40,48,66]	(A1-Cz) (A2-Cz) (2cm anterior C3-Cz) (2cm posterior C3-Cz) (2cm anterior C4-Cz) (2cm posterior C4-Cz) Only the first 2 channels are used in feedback	Band pass filter	1) Calculate a 500ms moving average to the EEG signals 2) Wavelet Transform, Mixed Filtering Method Feature selection : 1) GA 2) Zeros-Norm Optimization and Recursive Feature Elimination	1) Linear Threshold 2) SVMs 3) LDA 4) Z-scale based Discriminant Analysis
Wardsworth BCI [6,36]	Electrodes over the sensorimotor cortex area	1) CAR 2) Laplacian Reference 3) bipolar reference	Autoregressive spectral estimation	Linear Threshold

Table A.3, continued

Berlin BCI [25,38,67]	21 electrodes mounted over the motor and sensorimotor cortex and 6 frontal and occipital channels	Laplacian Filter	1) Window the data with a one-sided cos function and apply Fast Fourier Transform (FFT) filtering technique 2) AR and CSP	1) Regularized Fisher Discriminant 2) Fisher Discriminant 3) Sparse Fisher Discriminant 4) Support Vector Machines (SVMs) 5) k-Nearest-Neighbour
Asynchronous BCI System				
Asynchronous Graz BCI [9]	6 bipolar channels over cortical hand and foot area		Logarithmic band-power estimate. Feature selection: 1) GA	LDA
LF-ASD [22,41,59,68]	Bipolar: F_1-FC_1, F_z-FC_z, F_2-FC_2, FC_1-C_1, FC_z-C_z, FC_2-C_2	1)Energy Normalization 2) Bandpass filter from 1-4 Hz	Analysis of EEG 1-4 Hz using a bi-scale wavelet	Nearest neighbour 1-NN classifier on the features set modeled by a LVQ
ABI [23,69]	F3, F4, C3, C4, P3, P4, Cz, Pz	Surface Laplacian	PSD using Welch periodogram algorithm (average three 0.5s segments with 50% overlap)	1)Local Neural Classifier 2) Gaussian Statistical Classifier

APPENDIX B: Experimental Protocol

Appendix B-1 The Conventions of the Names of the Derived EEG Bipolar Channels

Table B.1 presents the conventions of the names of the derived EEG bipolar channels that are used throughout the present study. The channels were derived from the montage used in *Figure 2.3*.

Three bipolar channels were derived from the anterior, center and posterior of the electrodes in C3, C4 and CZ region respectively. The bipolar channels were named based on the electrode positions used in deriving the bipolar channels. The first two letters depict the two electrode positions: anterior (a), posterior (p) or center (c) of the C3, C4 or CZ region.

Table B.1. The conventions of the names of the derived EEG bipolar channels used in this study.

	Name of the channel	Electrode Positions
Region C3	Channel ac_C3 Channel ap_C3 Channel pc_C3	ac3, c3 ac3, pc3 pc3, c3
Region CZ	Channel ac_CZ Channel ap_CZ Channel pc_CZ	acz, cz acz, pcz pcz, cz
Region C4	Channel ac_C4 Channel ap_C4 Channel pc_C4	ac4, c4 ac4, pc4 pc4, c4

Appendix B-2 Electrodes Technical Applications

The head of the subject is measured by using the 10-20 International System of Electrode Placement to estimate the electrode locations. There are 21 electrodes according to the system. *Figure B.1* shows the electrode placements in the system.

A plastic metric measuring tape is used to measure the head and a red color, non-toxic skin marking pen is used to mark the head of the subject. Next, each location of the electrode placements marked is cleaned by rubbing the spot with the cleansing material that contains some abrasive substances to diminish the layer of natural oil on the scalp. The electrodes are then placed on the skin. The Ten20 conductive electrode paste is used to improve the contact between scalp and electrodes and reduce the electrode impedance.

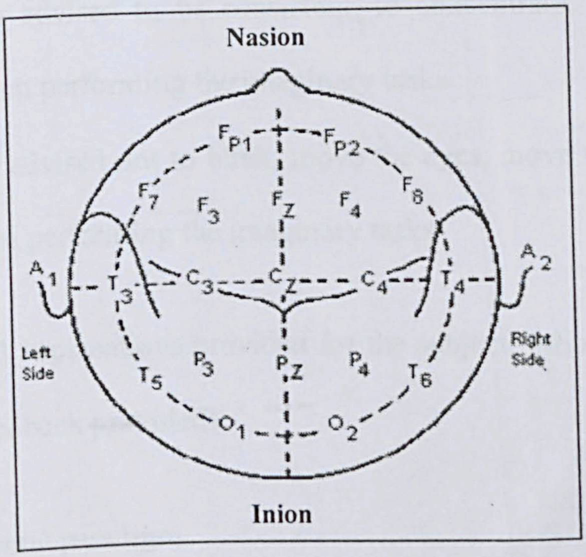


Figure B.1. The electrode placements in the International 10-20 System.

Measuring and maintaining good inter-electrode and electrode-scalp resistance is important to record high quality and artifacts-free EEG signals [91]. After applying each electrode on the scalp of the subject, the impedance is checked by using the EEG commercial system. Those electrodes with impedance more than 10 kΩ will be reapplied.

Appendix B-3 Explanations of the Experimental Protocol

The details of the experimental protocol explained to the new subjects before an offline experiment are as follows:-

- The number of electrodes used and the procedures of the technical applications.
- The experimental paradigm.
- The subject is advised to sit in a comfortable and relax position.
- The subject is given the freedom to choose to imagine by either visualizing the subject's own hand or foot moving or kinaesthetic imagery or the combination of both. However, the subject is encouraged to use kinaesthetic imagery because preliminary results showed that a more significant EEG changes could be detected by using kinaesthetic imagery.
- The subject is advised to be consistent, to concentrate, not to count and be motionless when performing the imaginary tasks.
- The subject is advised not to blink, move the eyes, move the feet or hands, bite and so on when performing the imaginary tasks.

The additional explanations provided for the subjects who are new in the online experiments (with feedback provided):-

- The experimental paradigm.
- The two mental tasks to use in the experiment.
- The objective of having the feedback system and how it works.
- The subject is requested not to move his or her eyes with the cursor's (feedback).
- In the application phase, the mental task used to make a selection and the principle of operation of the GUI in the application phase will be explained.

Appendix B-4 The Experimental Paradigm

The experimental paradigm used in the offline experiment and the classifier set-up phase of the online experiments is shown in *Figure 2.7*. In the offline experiments, there will be 5 sessions and three mental tasks (RIGHT, LEFT and FOOT) are performed by the subject whereas in the classifier set-up phase, only two of the selected mental tasks are used and there will be only 3 sessions.

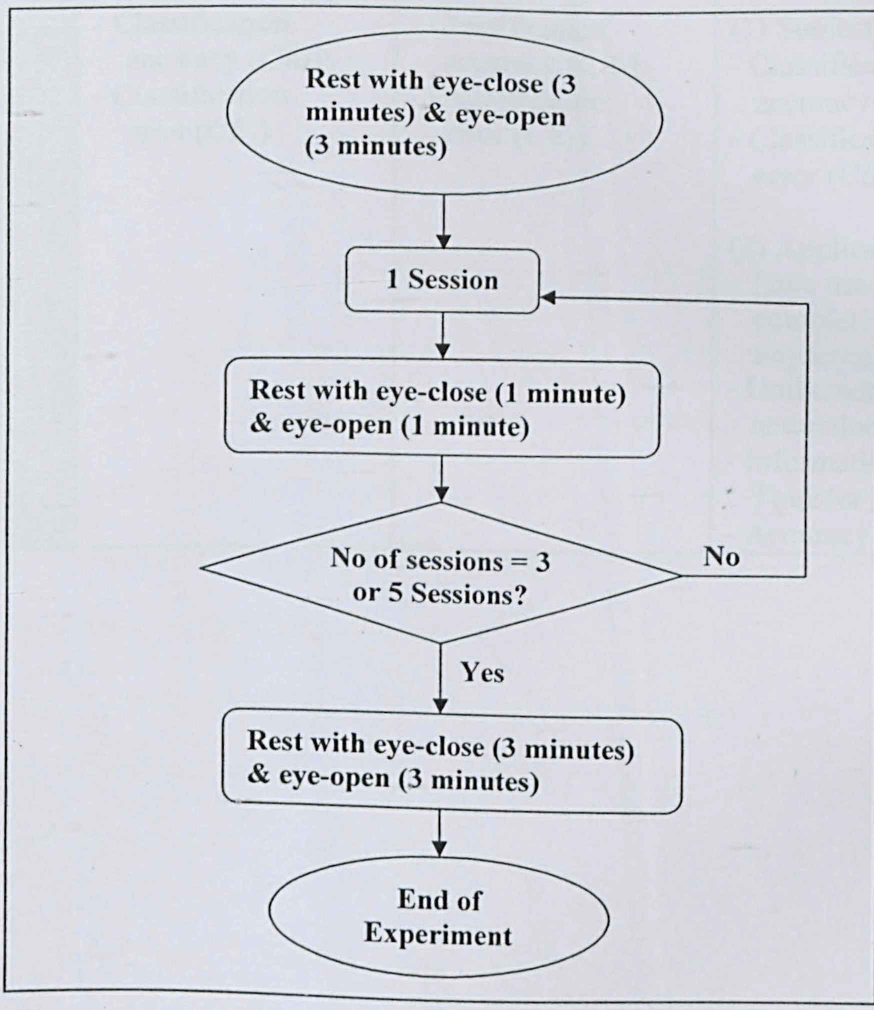


Figure B.2. The experimental paradigm.

Appendix B-5 The Three Experimental Stages

Table B.2. The details of the three experimental stages.

	Stage 1	Stage 2	Stage 3
Feedback system	Feedback system 1	Feedback system 1	Feedback system 2
Interface System	USB	Bluetooth	Bluetooth
Phase of online experiments involved	- Subject-training	- Subject-training	-Subject-training -Application
Parameters used for performance evaluation	- Classification accuracy (CR_1) - Classification error (CE_1)	- Classification accuracy (CR_1) - Classification error (CE_1)	(1) Subject-training - Classification accuracy (CR_2) - Classification error (CE_2) (2) Application - Time used to complete a test sequence (T_c) - Unintended activations (UIA) - Information Transfer Rate (ITR) - Accuracy

Appendix B-6 The Application-Based System Design

The descriptions on how the GUI of the application-based system operates are as follows:-

1) Initially, the GUI-A (*Figure B.3(a)*) is presented to the subject. The option appeared in the grey box will change every 5 seconds. If 'Hand' is selected, GUI-B1 (*Figure B.3(b)*) will be displayed. If 'Switch' is selected, GUI-B2 (*Figure B.4(b)*) will be displayed.
2) In GUI-B1, "GRAB" means grip; "3POD" means tripod; "PINCH" means pulp-to-pulp pinch; "KEYP" means key pinch. If the subject selected the desired option in the grey box (for example, PINCH), the text of 'PINCH' in the GUI (*Figure B.3(c)*) will be displayed to inform the successful selection. After the confirmation, 'OK-PINCH' will be displayed to inform the successful confirmation and an output signal will be sent to a Fuzzy Logic Controller to move the prosthetic hand. The GUI-C (*Figure B.3(d)*) will be displayed and wait for the subject to reset the prosthetic hand.
3) "RESET" in the GUI-C means to move the prosthetic hand back to its original position. After the activation of the 'RESET', the prosthetic hand will reset and the GUI-A will be redisplayed again.

Figure B.4 shows GUI-C. If the subject wants to activate the LED, the subject has to select 'Switch' (*Figure B.4(a)*) and to be followed by the LED he or she wants to activate (*Figure B.4(b)*). The principle of operations of the GUIs in *Figure B.4* is similar to the one explained in 2) above. After the LED is activated, GUI-A will be redisplayed again. The LED will be switched off if the other different LED is switched on. The system operation is shown in *Figure B.5*.

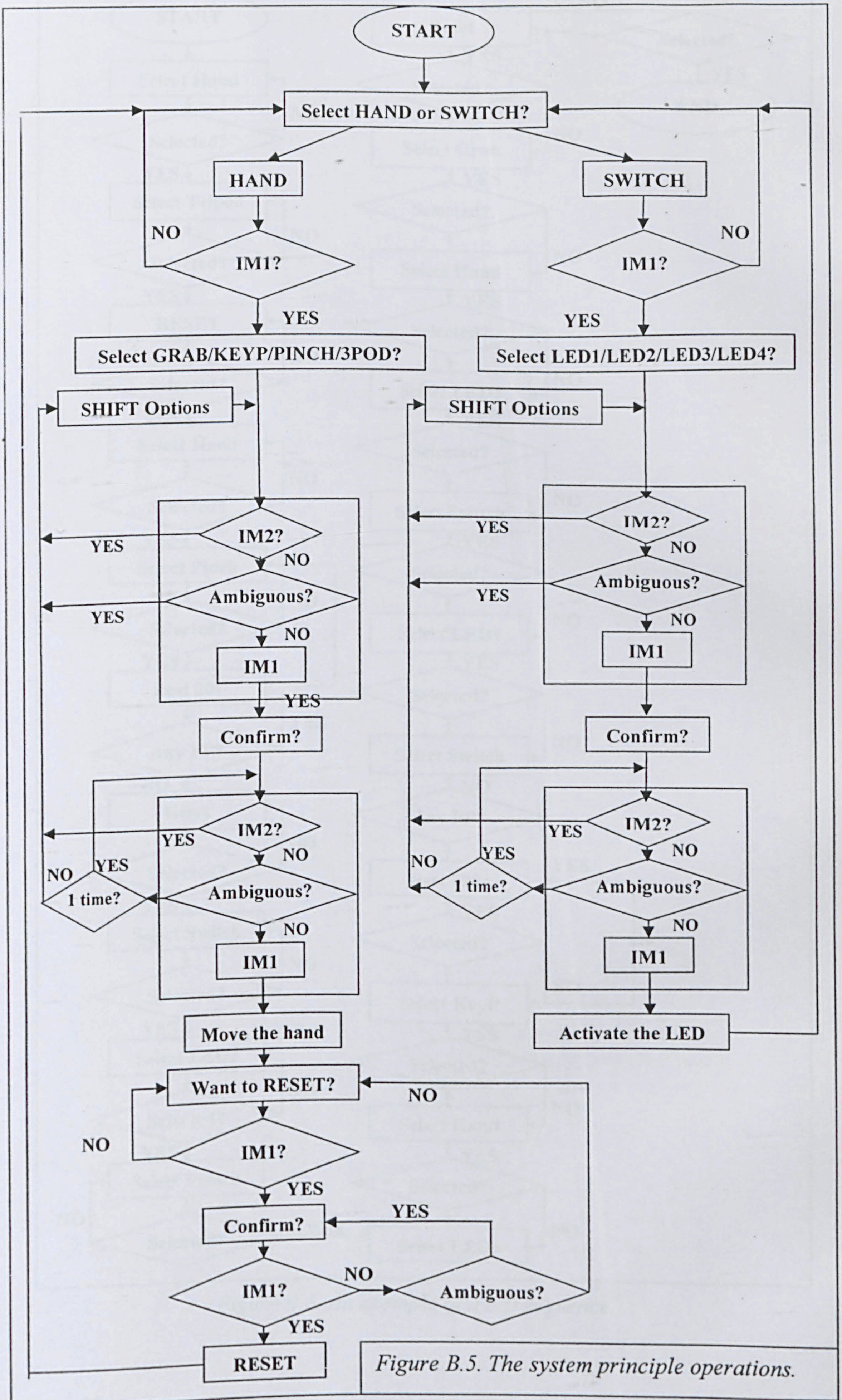


Figure B.5. The system principle operations.

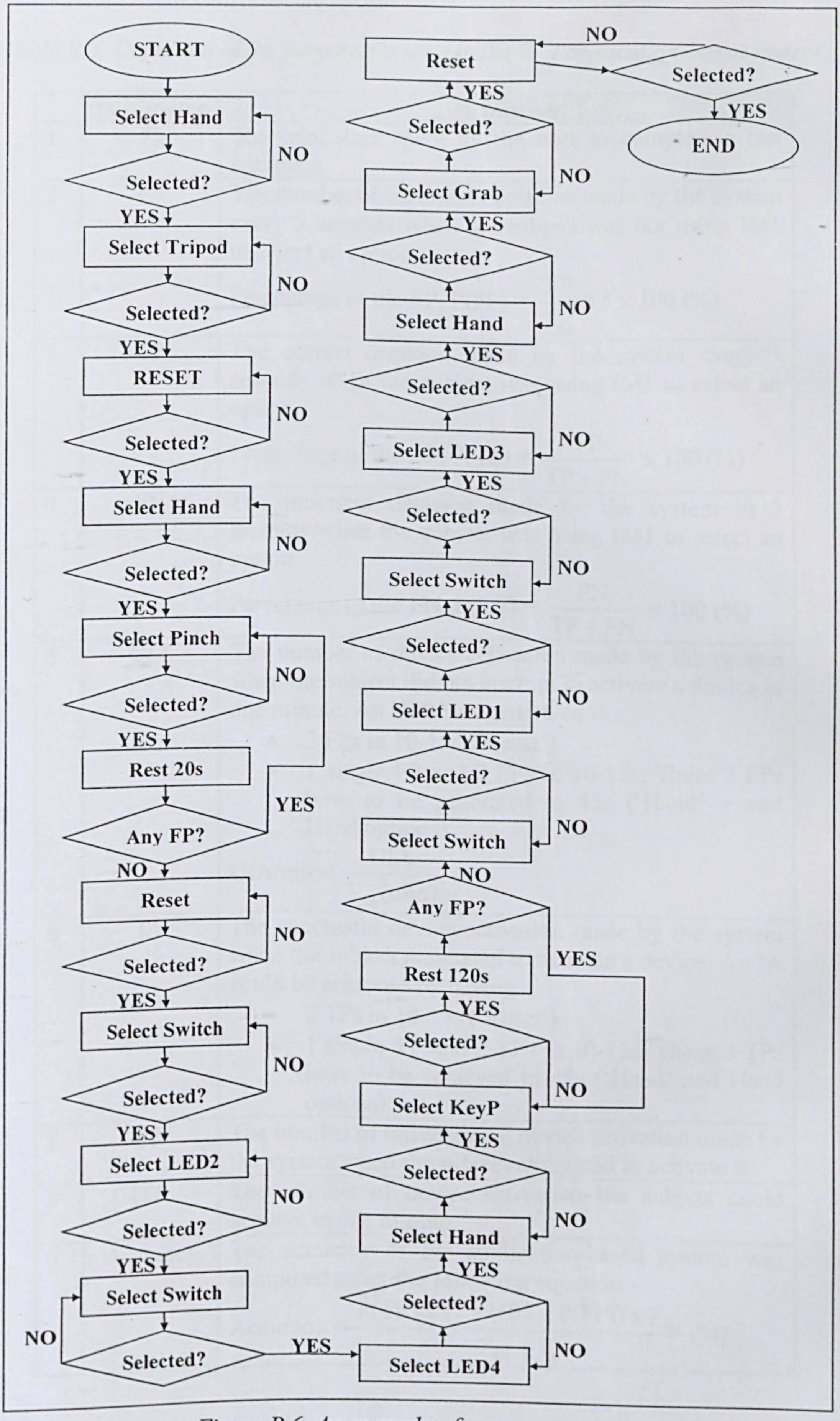


Figure B.6. An example of a test sequence.

Table B.3. Definition of the parameters used in the BCI application-based system.

	Parameter	Definition
1	T_c	The total time spent by the user to complete a test sequence
2	FP	The number of incorrect decisions made by the system every 5 seconds when the subject was not using IM1 to select an option. Percentage of the FP, $P(FP) = \frac{FP}{T_{NA}} \times 5 \times 100$ (%)
3	TP	The correct decision made by the system every 5 seconds when the subject was using IM1 to select an option. Percentage of the TP, $P(TP) = \frac{TP}{TP + FN} \times 100$ (%)
4	FN	The incorrect decision made by the system in 5 seconds when the subject was using IM1 to select an option. Percentage of the FN, $P(FN) = \frac{FN}{TP + FN} \times 100$ (%)
5	UIA	The number of device activation made by the system when the subject did not attempt to activate a device in one minute. An UIA was generated if:- • 2 FPs in 10-15s ('Reset') • 1 single FP and 2 FPs in 10-15s. These 3 FPs have to be generated in 45s ('Hand' + and Hand options) $UIA/min = \frac{UIA}{T_{NA}(min)}$
6	IA	The successful device activation made by the system when the subject attempted to activate a device. An IA could be achieved by having:- • 2 TPs in 10-15s ('Reset') • 1 single TP and 2 TPs in 10-15s. These 3 TPs have to be achieved in 45s ('Hand' and Hand options)
7	FA	The number of unsuccessful device activation made by the system when the subject attempted to activate it
8	ITR	The number of device activation the subject could achieve in one minute.
9	Accuracy	The accuracy of the application-based system was computed using the following equation:- $Accuracy = \frac{P(TP) \times T_S + (100 - P(FP)) \times T_{NA}}{T_{NA} + T_S}$ (%)

APPENDIX C: Online Signal processing

Appendix C-1 The Algorithm of the Burg's Method

Table C.1. Burg's method.

1) Minimize the Prediction error, $\varepsilon = \sum_{n=p}^{N-1} [e_m^{\ f}(n)^2 + e_m^{\ b}(n)^2]$:-

$$\frac{\partial \varepsilon}{\partial \gamma_m} = 2\sum_{n=p}^{N-1}[e_m^{\ f}(n)\frac{\partial e_m^{\ f}(n)}{\partial \gamma_m} + e_m^{\ b}(n)\frac{\partial e_m^{\ b}(n)}{\partial \gamma_m}] = 0$$

Where $e_m^{\ f}(n)$ = forward prediction error

$e_m^{\ b}(n)$ = backward prediction error

γ_m = the reflection coefficient

N = the number of samples

2) Mathematical solution to find the reflection coefficient:-

$$\frac{\partial \varepsilon}{\partial \gamma_m} = 2\sum_{n=p}^{N-1}[e_m^{\ f}(n)\frac{\partial e_m^{\ f}(n)}{\partial \gamma_m} + e_m^{\ b}(n)\frac{\partial e_m^{\ b}(n)}{\partial \gamma_m}] = 0$$

$$\sum_{n=p}^{N-1}[e_m^{\ f}(n)e_m^{\ b}(n-1) + e_m^{\ b}(n)e_m^{\ b}(n)] = 0$$

$$\therefore e_m^{\ f}(n) = e_{m-1}^{\ f}(n) - \gamma_m e_{m-1}^{\ b}(n-1) \text{ and } e_m^{\ b}(n) = e_{m-1}^{\ b}(n-1) - \gamma_m e_{m-1}^{\ f}(n)$$

$$\sum_{n=p}^{N-1}[(e_{m-1}^{\ f}(n) - \gamma_m e_{m-1}^{\ b}(n-1))e_{m-1}^{\ b}(n-1) + (e_{m-1}^{\ b}(n-1) - \gamma_m e_{m-1}^{\ f}(n))e_{m-1}^{\ f}(n)] = 0$$

$$\therefore \gamma_m = \frac{2\sum_{n=p}^{N-1} e_{m-1}^{\ f}(n)e_{m-1}^{\ b}(n-1)}{\sum_{n=p}^{N-1}[e_{m-1}^{\ f}(n)^2 + e_{m-1}^{\ b}(n-1)^2]}, \gamma_m < 1$$

3) Use the Levinson-Durbin algorithm to obtain the AR coefficients:-

$$\begin{pmatrix} 1 \\ a_{m,1} \\ a_{m,2} \\ \cdot \\ a_{m,m} \end{pmatrix} = \begin{pmatrix} 1 \\ a_{m-1,1} \\ a_{m-1,2} \\ \cdot \\ 0 \end{pmatrix} - \gamma_m \begin{pmatrix} 1 \\ a_{m-1,m-1} \\ a_{m-1,m-2} \\ \cdot \\ 1 \end{pmatrix}$$

Appendix C-2 The AIC ANOVA and Post-Hoc Test Tables

Table C.2. AIC ANOVA Table.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	15155925	9	1683991.700	979.271	.000
Within Groups	1702441	990	1719.637		
Total	16858366	999			

Table C.3. Homogenous Subsets for the AIC of AR model order 1-10.

AR Order	Subset for alpha=0.01			
	1	2	3	4
1	906.65			
2		860.39		
3			623.18	
4			619.09	
5			614.11	
6				567.17
7				567.10
8				562.21
9				556.31
10				556.74
Sig	1.000	1.000	0.146	0.100

Appendix C-4 Feedback Step Size

The step size (ranged from 0-4) of the feedback slider's cursor used is depending on the magnitude of LDA_{output}. *Figure C.1* illustrates the step size used in correspond to the value of $|LDA_{output}|$.

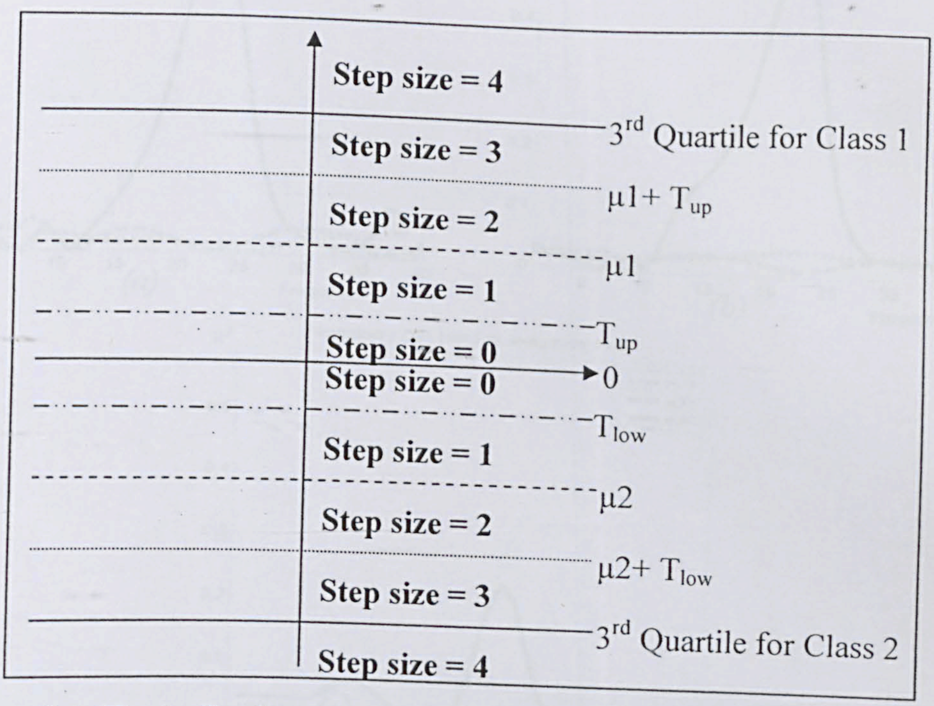


Figure C.1. The feedback step size used is dependent on the value of $|LDA_{output}|$.

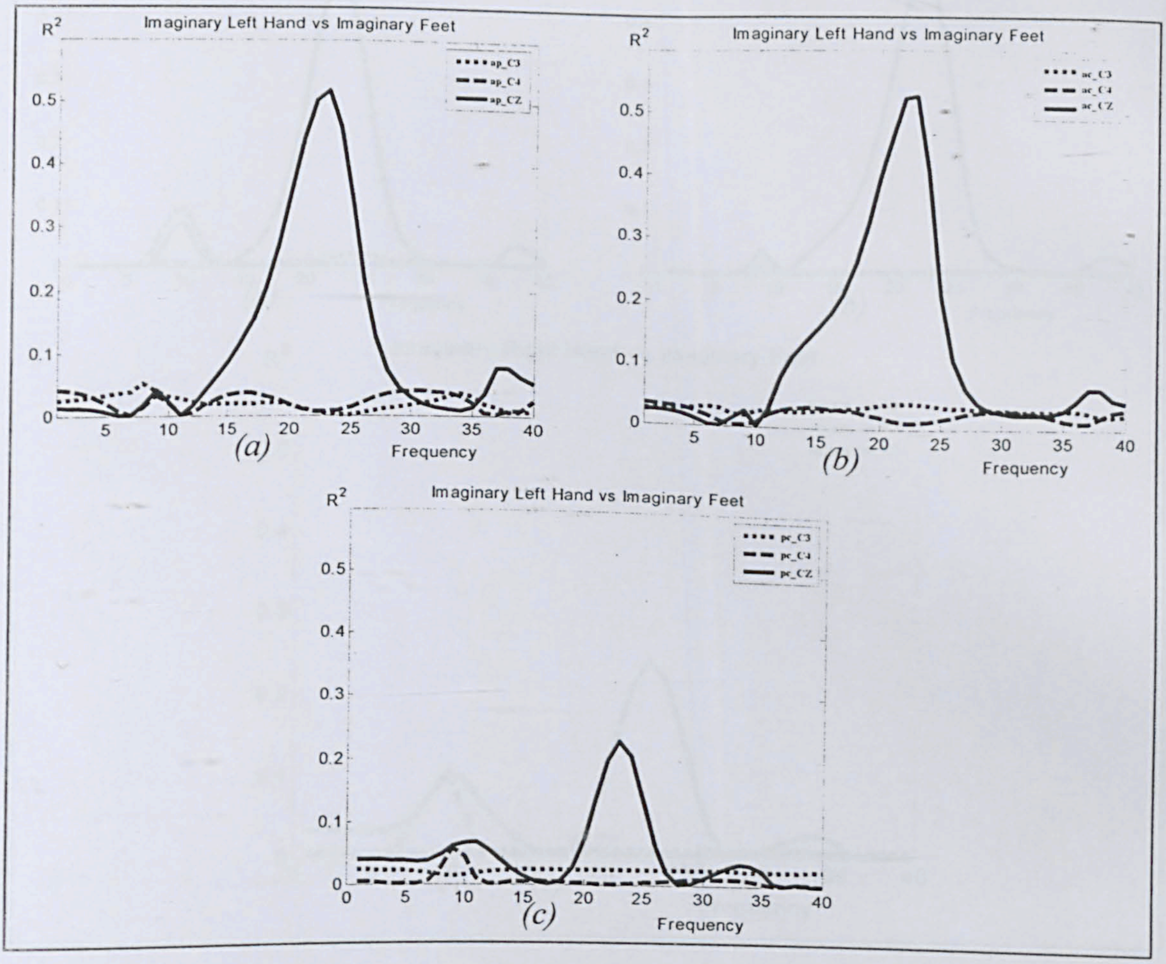


Figure D.1. R^2 spectra of the 9 bipolar montages for the discrimination of LEFT and FOOT: (a) R^2 spectra of channel ap_C3, ap_C4 and ap_CZ. (b) R^2 spectra of channel ac_C3, ac_C4 and ac_CZ. (c) R^2 spectra of channel pc_C3, pc_C4 and pc_CZ.

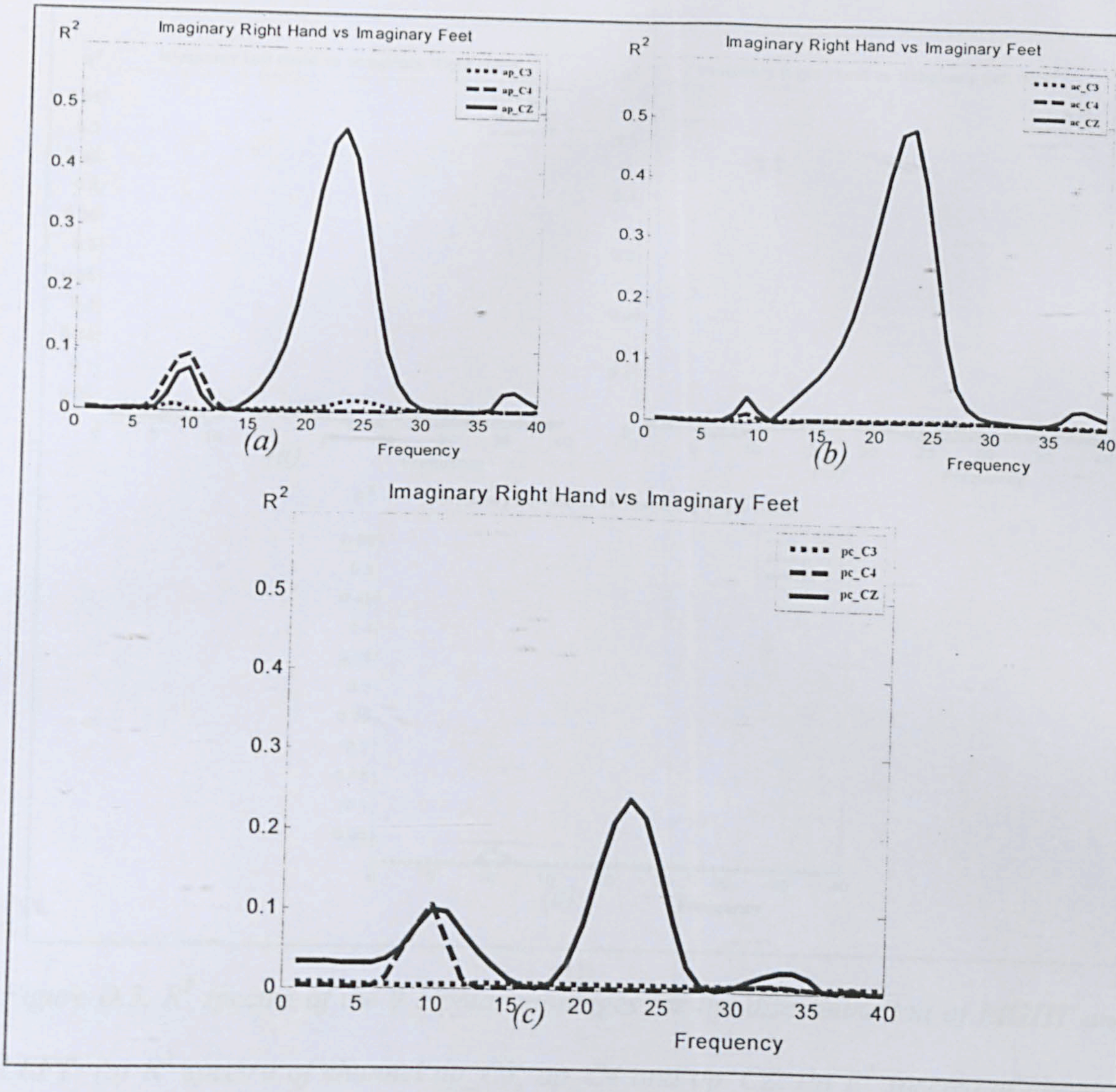


Figure D.2. R^2 spectra of the 9 bipolar montages for the discrimination of RIGHT and FOOT: (a) R^2 spectra of channel ap_C3, ap_C4 and ap_CZ. (b) R^2 spectra of channel ac_C3, ac_C4 and ac_CZ. (c) R^2 spectra of channel pc_C3, pc_C4 and pc_CZ.

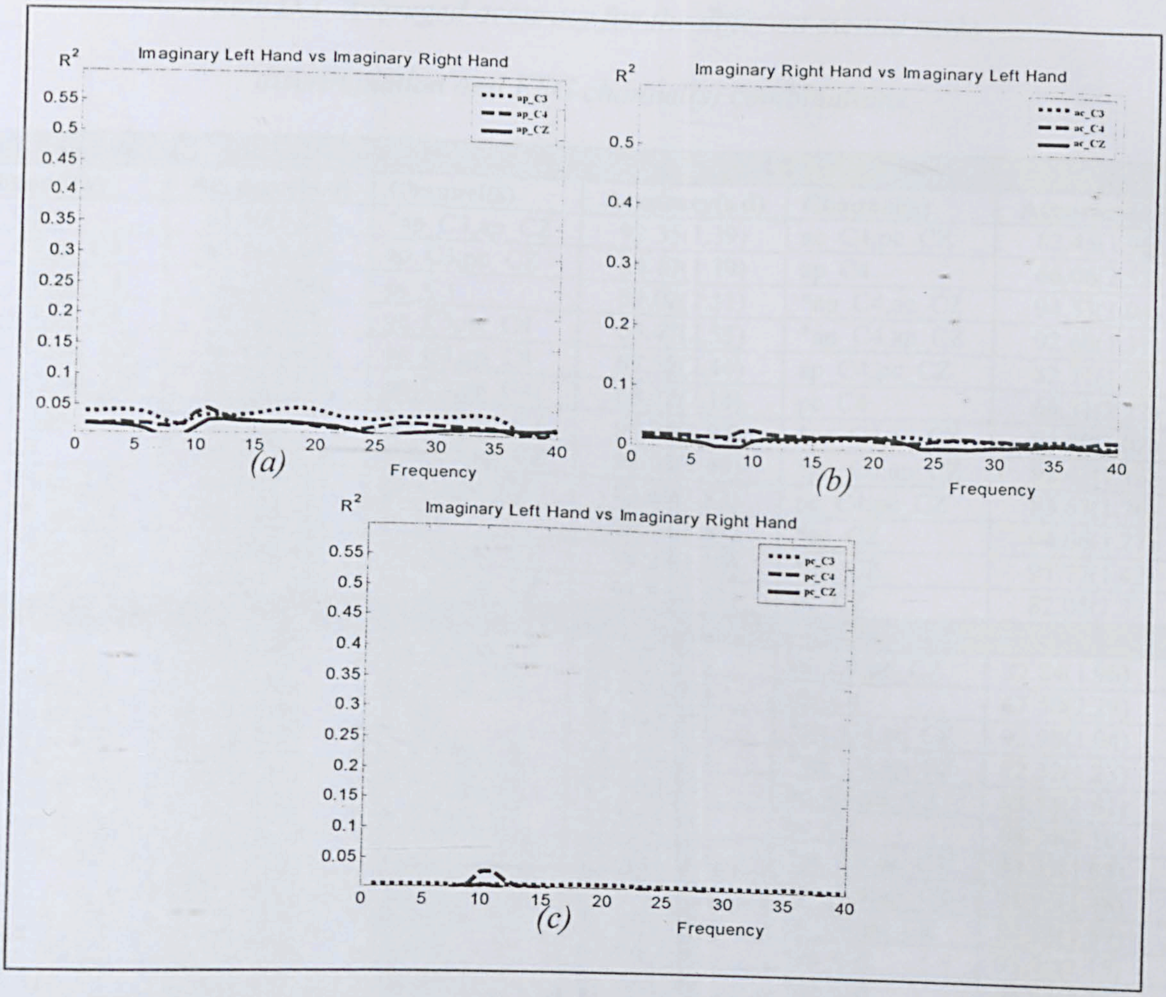


Figure D.3. R^2 spectra of the 9 bipolar montages for the discrimination of RIGHT and LEFT: (a) R^2 spectra of channel ap_C3, ap_C4 and ap_CZ. (b) R^2 spectra of channel ac_C3, ac_C4 and ac_CZ. (c) R^2 spectra of channel pc_C3, pc_C4 and pc_CZ.

Table D.1. Averaged accuracy for the different mental tasks discrimination and EEG channel(s) combinations.

LEFT and FOOT					
Channel(s)	**Accuracy(s.d)**	**Channel(s)**	**Accuracy(s.d)**	**Channel(s)**	**Accuracy(s.d)**
ac_C3	63.40(2.25)	*ap_C3,ap_CZ	92.35(1.39)	ac_C4,pc_CZ	82.45(1.96)
ac_C3,ac_C4	65.76(2.40)	ap_C3,pc_CZ	84.17(1.79)	ap_C4	66.06(2.53)
ac_C3,ap_C4	70.23(2.06)	pc_C3	59.02(2.31)	*ap_C4,ac_CZ	94.53(1.04)
ac_C3,pc_C4	69.32(2.28)	pc_C3,ac_C4	63.47(2.53)	*ap_C4,ap_CZ	92.60(1.31)
*ac_C3,ac_CZ	94.33(1.02)	pc_C3,ap_C4	67.52(2.44)	ap_C4,pc_CZ	82.71(1.90)
*ac_C3,ap_CZ	91.76(1.25)	pc_C3,pc_C4	68.32(2.14)	pc_C4	66.31(2.22)
ac_C3,pc_CZ	82.47(1.64)	*pc_C3,ac_CZ	94.26(1.07)	*pc_C4,ac_CZ	94.89(1.02)
ap_C3	64.29(2.11)	*pc_C3,ap_CZ	92.08(1.49)	*pc_C4,ap_CZ	92.42(1.16)
ap_C3,ac_C4	66.81(2.31)	pc_C3,pc_CZ	82.69(1.83)	pc_C4,pc_CZ	83.67(1.76)
ap_C3 ap_C4	66.24(2.32)	ac_C4	59.89(2.47)	*ac_CZ	94.06(1.27)
ap_C3,pc_C4	68.88(2.40)	*ac_C4,ac_CZ	94.27(1.10)	*ap_CZ	91.77(1.42)
*ap_C3,ac_CZ	94.31(1.10)	*ac_C4,ap_CZ	91.85(1.51)	pc_CZ	82.05(1.77)
RIGHT and FOOT					
ac_C3	57.48(2.16)	*ap_C3,ap_CZ	91.48(1.35)	ac_C4,pc_CZ	82.84(1.96)
ac_C3,ac_C4	63.11(2.46)	ap_C3,pc_CZ	83.83(1.91)	ap_C4	67.50(2.29)
ac_C3,ap_C4	68.87(2.34)	pc_C3	57.10(2.27)	*ap_C4,ac_CZ	93.98(1.04)
ac_C3,pc_C4	70.33(2.32)	pc_C3,ac_C4	64.15(2.07)	*ap_C4,ap_CZ	92.32(1.23)
*ac_C3,ac_CZ	94.05(1.14)	pc_C3,ap_C4	67.91(2.27)	ap_C4,pc_CZ	83.75(1.61)
*ac_C3,ap_CZ	91.44(1.23)	pc_C3,pc_C4	70.53(1.99)	pc_C4	68.74(2.10)
ac_C3,pc_CZ	82.92(1.75)	*pc_C3,ac_CZ	93.70(1.15)	*pc_C4,ac_CZ	94.27(1.03)
ap_C3	59.99(2.33)	*pc_C3,ap_CZ	91.70(1.46)	*pc_C4,ap_CZ	91.95(1.48)
ap_C3,ac_C4	66.58(1.81)	pc_C3,pc_CZ	83.26(1.90)	pc_C4,pc_CZ	84.08(1.69)
ap_C3 ap_C4	69.10(2.00)	ac_C4	62.24(2.38)	*ac_CZ	93.70(1.15)
ap_C3,pc_C4	70.32(2.01)	*ac_C4,ac_CZ	93.76(1.25)	*ap_CZ	91.64(1.38)
*ap_C3,ac_CZ	93.83(1.16)	*ac_C4,ap_CZ	91.51(1.41)	pc_CZ	82.61(1.95)
RIGHT vs LEFT					
ac_C3	57.46(2.46)	ap_C3,ap_CZ	61.34(2.66)	ac_C4,pc_CZ	57.77(2.30)
ac_C3,ac_C4	59.07(2.41)	ap_C3,pc_CZ	60.25(2.51)	ap_C4	54.92(2.50)
ac_C3,ap_C4	59.29(2.51)	pc_C3	53.39(2.78)	ap_C4,ac_CZ	57.72(2.30)
ac_C3,pc_C4	58.59(2.28)	pc_C3,ac_C4	56.49(2.26)	ap_C4,ap_CZ	59.07(2.16)
ac_C3,ac_CZ	60.10(2.32)	pc_C3,ap_C4	56.52(2.58)	ap_C4,pc_CZ	55.47(2.16)
ac_C3,ap_CZ	61.31(2.32)	pc_C3,pc_C4	55.19(2.22)	pc_C4	55.10(2.60)
ac_C3,pc_CZ	57.96(2.17)	pc_C3,ac_CZ	57.00(2.26)	pc_C4,ac_CZ	57.38(2.16)
ap_C3	56.72(3.01)	pc_C3,ap_CZ	59.26(2.49)	pc_C4,ap_CZ	58.34(2.64)
ap_C3,ac_C4	60.34(2.50)	pc_C3,pc_CZ	56.52(2.29)	pc_C4,pc_CZ	54.00(2.43)
ap_C3 ap_C4	60.78(2.36)	ac_C4	56.22(2.19)	ac_CZ	56.51(1.93)
ap_C3,pc_C4	59.14(2.73)	ac_C4,ac_CZ	58.96(2.16)	ap_CZ	57.67(2.60)
ap_C3,ac_CZ	61.33(2.11)	ac_C4,ap_CZ	60.09(2.60)	pc_CZ	54.50(2.26)

*EEG channel(s) with accuracy more than 90%
s.d : standard deviation

Table D.2. ANOVA Table for the mental tasks combination of LEFT and FOOT.

	Sum of Squares	df	Mean Square	F	Sig
Between Groups	1899.482	13	146.11	95.298	.000
Within Groups	2125.062	1386	1.533		
Total	4042.544	1399			

Table D.3. ANOVA Table for the mental tasks combination of RIGHT and FOOT.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1752.177	13	134.783	85.634	.000
Within Groups	2181.476	1386	1.574		
Total	3933.653	1399			

Table D.4. Homogenous Subsets for the mental tasks combination of LEFT and FOOT.

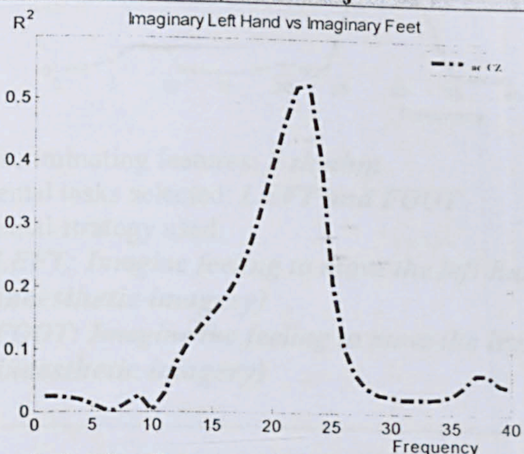
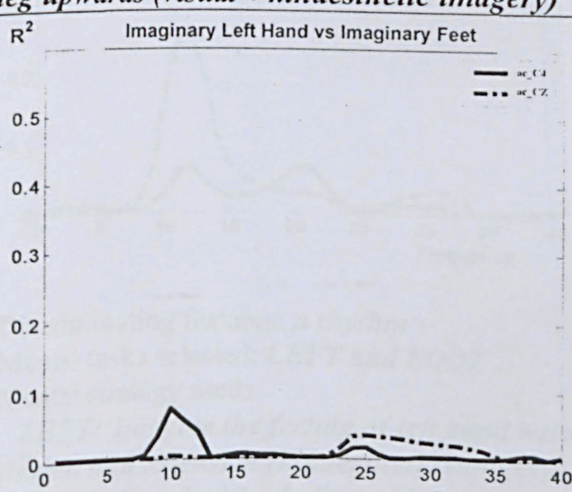
Channel(s)	Subset for alpha=0.01				
	1	2	3	4	5
ac_C3 and ap_CZ	91.76				
ap_CZ	91.76				
ac_C4 and ap_CZ	91.85				
pc_C3 and ap_CZ	92.08	92.08			
ap_C3 and ap_CZ		92.35	92.35		
pc_C4 and ap_CZ		92.42	92.42		
ap_C4 and ap_CZ			92.60		
ac_CZ				94.06	
pc_C3 and ac_CZ				94.26	
ac_C4 and ac_CZ				94.27	
ap_C3 and ac_CZ				94.31	
ac_C3 and ac_CZ				94.33	
ap_C4 and ac_CZ				94.53	94.53
pc_C4 and ac_CZ					94.89
Sig	.102	.066	.181	.015	.042

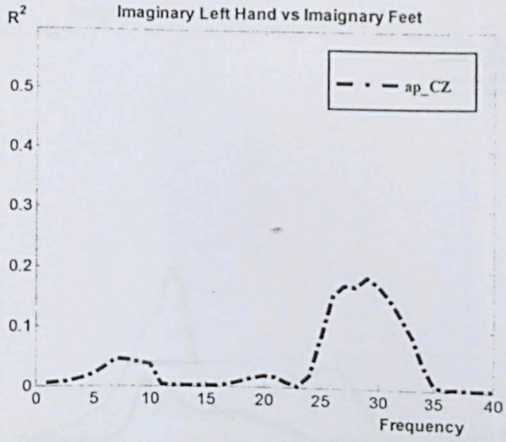
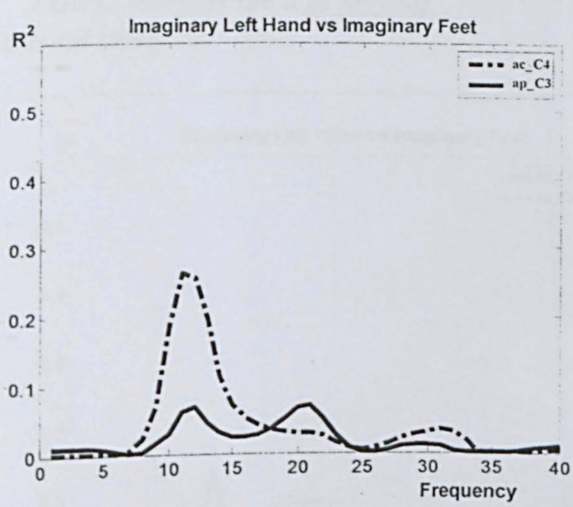
Table D.5. Homogenous Subsets for the

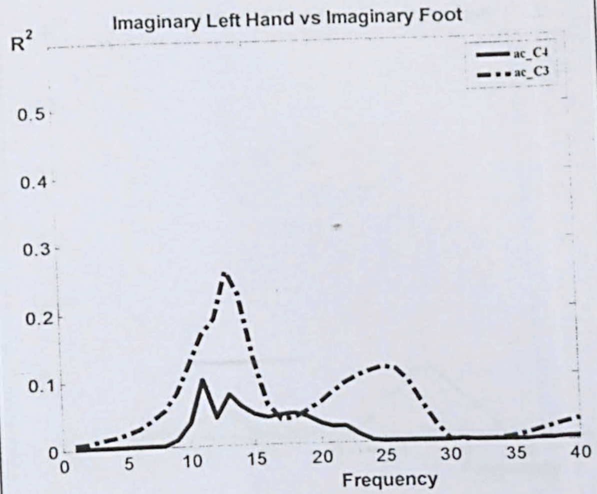
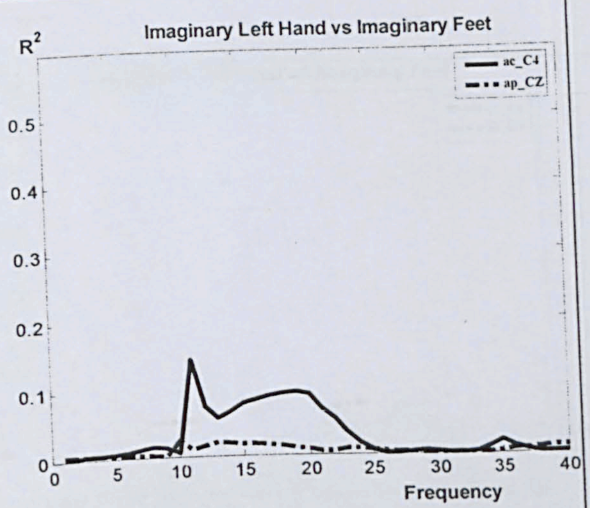
mental tasks combination of RIGHT and FOOT.

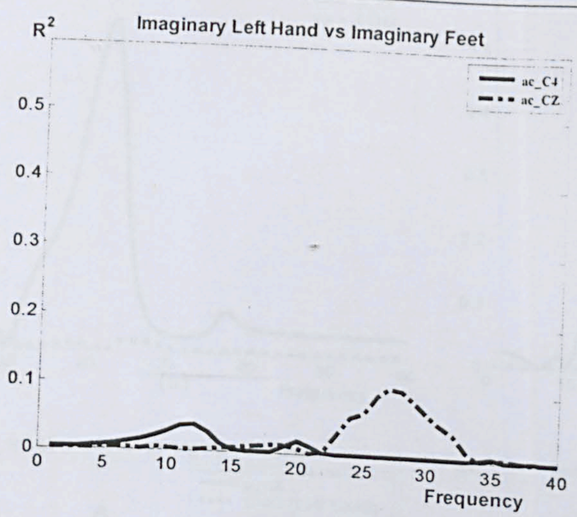
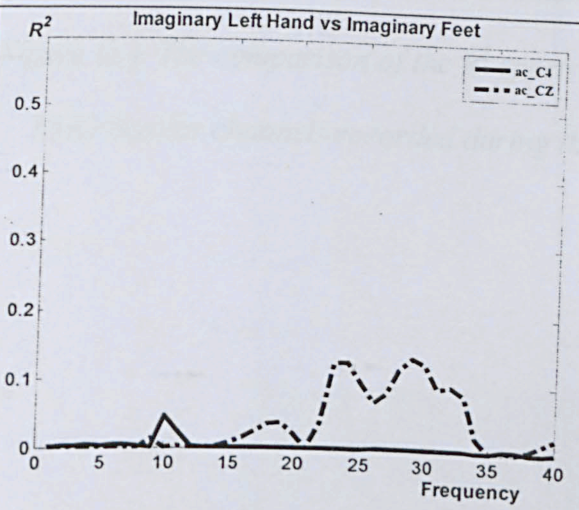
Channel(s)	Subset for alpha=0.01				
	1	2	3	4	5
ac_C3 and ap_CZ	91.44				
ap_C3 and ap_CZ	91.48	91.48			
ac_C4 and ap_CZ	91.51	91.51			
ap_CZ	91.64	91.64			
pc_C3 and ap_CZ	91.70	91.70			
pc_C4 and ap_CZ		91.95	91.95		
ap_C4 and ap_CZ			92.32		
pc_C3 and ap_CZ				93.70	
ac_CZ				93.70	
ac_C4 and ac_CZ				93.76	
ap_C3 and ac_CZ				93.83	93.83
ap_C4 and ac_CZ				93.98	93.98
ac_C3 and ac_CZ				94.05	94.05
pc_C4 and ac_CZ					94.27
Sig	.193	.017	.036	.086	.022

Table D.6. The R^2 spectra, the discriminating features, the selected mental tasks, the mental strategy used, the selected EEG channel(s) and the averaged accuracy of the LDA 10x10 fold cross validation for all the subjects participated in the offline experiment.

Subject	R^2 Spectral/ Discriminating Features/ Selected Metal Tasks/Mental Strategy used by the subject	EEG Channels	Accuracy
F1	 Discriminating features: ***β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the left hand playing piano (visual Imagery)*** ***FOOT: Imagine the feeling of moving the leg upwards (visual + kinaesthetic imagery)***	ac_CZ	94.06%
F2	 Discriminating features: ***μ and β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the left hand fingers moved in certain sequence (kinaesthetic imagery)*** ***FOOT: Imagine the legs stepping right and left (kinaesthetic imagery)***	ac_C4, ac_CZ	65.12%

F3	 Discriminating features: ***β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine feeling to move the left hand (kinaesthetic imagery)*** ***FOOT: Imagine the feeling to move the leg (kinaesthetic imagery)***	ap_CZ	79.46%
F4	 Discriminating features: ***μ rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the feeling of left hand wrist flexion and extension (kinaesthetic imagery)*** ***FOOT: Imagine the feeling of legs when the legs were playing the piano paddles (kinaesthetic imagery)***	ap_C3, ac_C4	84.18%

F5	 Discriminating features: ***μ and β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the feeling to the hand when the hand was not allowed to move (kinaesthetic imagery)*** ***FOOT: Imagine the legs moving (visual imagery)***	ac_C3, ac_C4	77.08%
F6	 Discriminating features: ***μ and β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the left hand playing piano with feeling (kinaesthetic imagery)*** ***FOOT: Imagine the feeling of legs moving during swimming (kinaesthetic imagery)***	ac_C4, ap_CZ	76.47%

F7	 Discriminating features: ***μ and β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the feeling of left hand moving to left and right (kinaesthetic imagery)*** ***FOOT: Imagine the feeling of legs moving (kinaesthetic imagery)***	ac_C4, ac_CZ	68.47%
M1	 Discriminating features: ***μ and β rhythm*** Mental tasks selected: ***LEFT and FOOT*** Mental strategy used: ***LEFT: Imagine the feeling of left hand pulling a load (kinaesthetic imagery)*** ***FOOT: Imagine the feeling to move the legs (kinaesthetic imagery)***	ac_C4, ac_CZ	79.77%

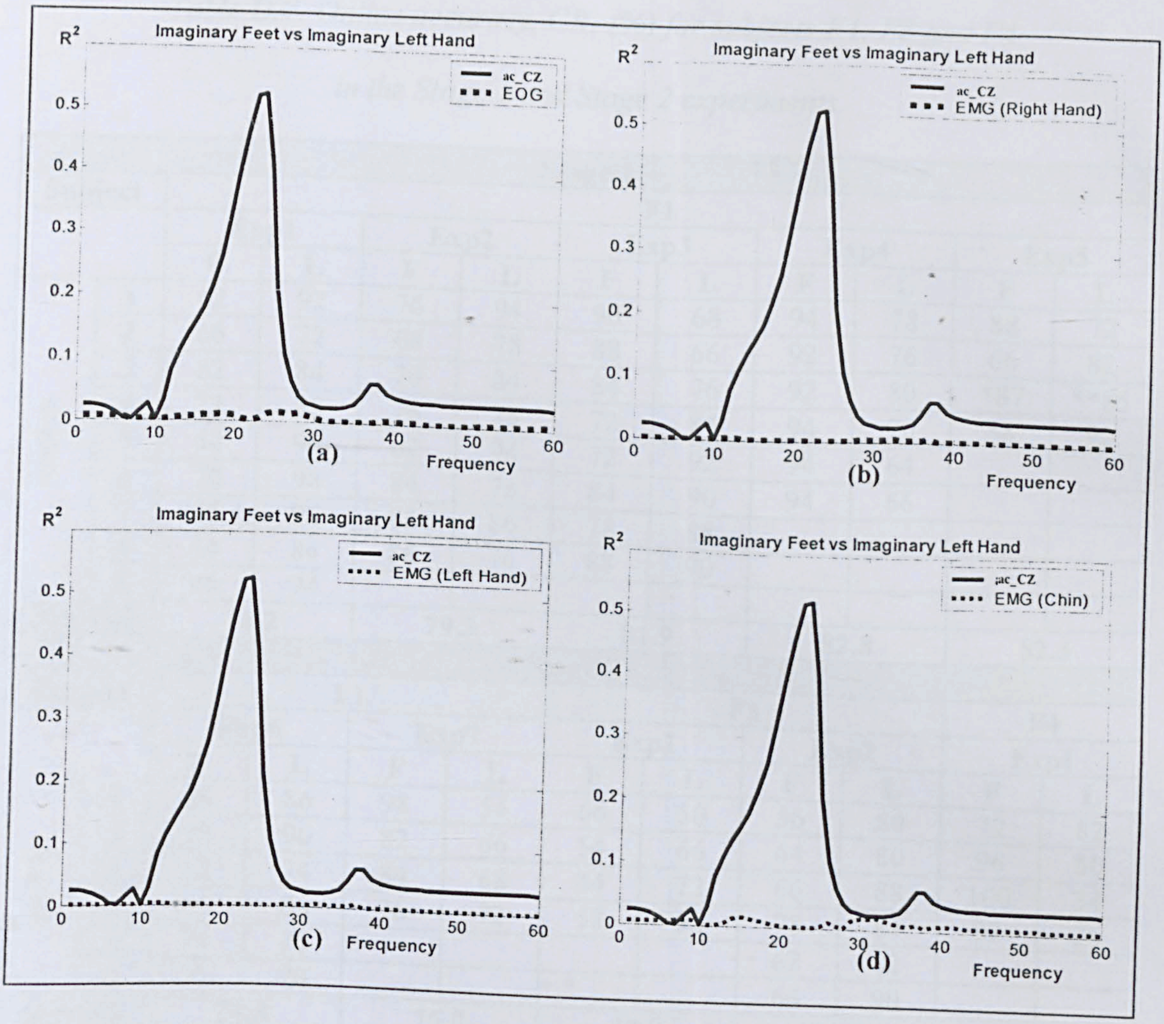


Figure D.4. The comparison of the R^2 spectrum of ac_CZ, EOG and EMG bipolar channels recorded during the offline experiment.

Table D.7. Online accuracy, CR_1 (%) for subjects F1, F3 and F4 in the Stage 1 and Stage 2 experiments.

Subject		Stage 1									
		F1									
		Exp1		Exp2		Exp3		Exp4		Exp5	
		F	L	F	L	F	L	F	L	F	L
Session	1	62	92	76	94	90	68	94	78	88	72
	2	66	72	68	78	88	66	92	76	66	82
	3	82	84	70	84	84	76	92	80	*87	**85
	4	72	88	76	76	72	84	94	70	88	92
	5	54	96	62	94	72	92	94	64		
	6	70	98	84	76	84	90	94	66		
	7	66	96	82	86	78	88				
	8	50	84	86	76	88	90				
	9	46	94								
Average		76.2		79.3		81.9		82.8		82.3	

Subject		Stage 2									
		F1				F3				F4	
		Exp6		Exp7		Exp1		Exp2		Exp1	
		F	L	F	L	F	L	F	L	F	L
Session	1	66	86	98	54	66	50	56	80	72	82
	2	38	96	82	66	54	66	64	80	96	40
	3	62	74	84	68	44	72	66	88	100	34
	4	64	86	76	72	58	52	78	84	92	26
	5	74	70					62	82		
	6	76	70					64	90		
Average		71.8		75.0		57.8		74.5		68.1	

Note: *9 trials, **8 trials
The L and F in the tables depict the LEFT and FOOT trials respectively and Exp depicts Experiment.

Table D.8. Online accuracy, CR_1 (%) for subject F1 in the two experiments that used the LDA set up in Exp3.

		F1			
		Exp3a (31, January, 2005)		Exp3b (22, February, 2005)	
		F	L	F	L
Session	1	75	75	88	72
	2	82	88	88	78
	3	78	90	72	94
	4	58	90	84	84
	5	62	92		
	6	24	94		
	7	66	92		
Average		76.1		82.5	

Table D.9. System performance on the contaminated EEG trials for subjects F1, F3 and F4.

Subject		**F1**					
		Exp5		**Exp6**		**Exp7**	
		F	L	F	L	F	L
Session	1	- (0)	- (0)	40(2)	87(3)	85(4)	40(2)
	2	60(2)	- (0)	- (0)	95(4)	70(2)	40(1)
	3	90(7)	94(25)	52(5)	80(2)	100(1)	70(2)
	4	73(3)	- (0)	90(2)	- (0)	64(5)	50(2)
	5			- (0)	80(1)		
	6			- (0)	60(1)		
Average		**89.7**		**73.0**		**66.3**	
Subject		**F3**				**F4**	
		Exp1		**Exp2**		**Exp1**	
		F	L	F	L	F	L
Session	1	73(3)	55(8)	87(3)	87(3)	60(2)	- (0)
	2	72(5)	60(2)	70(2)	80(7)	-99(3)	- (0)
	3	35(4)	60(2)	- (0)	89(7)	- (0)	54(2)
	4	- (0)	90(2)	75(4)	77(1)	- (0)	- (0)
	5			- (0)	90(2)		
	6			- (0)	60(1)		
Average		**60.8**		**81.9**		**75.0**	

Note: The number in the bracket is the number of contaminated EEG trials in that session.

Table D.10. Overall system performance for subjects F1, F3 and F4 when both the contaminated and non-contaminated EEG trials were classified.

Subject		**F1**					
		Exp5		**Exp6**		**Exp7**	
		F	L	F	L	F	L
Session	1	88	72	62	86	94	52
	2	65	82	38	96	80	64
	3	88	92	59	75	85	68
	4	85	92	68	86	72	68
	5			74	71		
	6			76	69		
Average		**84.5**		**72.0**		**73.33**	
Subject		**F1**				**F4**	
		Exp1		**Exp2**		**Exp5**	
		F	L	F	L	F	L
Session	1	68	49	63	82	70	82
	2	60	65	65	80	95	40
	3	41	70	66	88	100	30
	4	58	58	77	84	92	26
	5			62	83		
	6			64	87		
Average		**57.4**		**76.0**		**67.1**	

Table D.11. System performance, CR_2 (%) for subjects F1, F3 and F4 using Approach 1.

Subject		F1									
		Exp1		Exp2		Exp3		Exp4		Exp5	
		F	L	F	L	F	L	F	L	F	L
Session	1	70	100	90	100	90	90	100	100	100	100
	2	60	80	90	90	100	80	100	80	67	80
	3	90	90	70	100	100	100	100	90	100	97
	4	70	90	70	80	90	100	100	100	100	100
	5	70	100	80	100	70	100	100	80		
	6	90	100	100	90	90	100	100	70		
	7	70	100	90	90	90	100				
	8	30	90	100	100	100	100				
	9	40	100								
Average		80.0		90.0		93.8		93.3		94.0	

Subject		F1				F3				F4	
		Exp6		Exp7		Exp1		Exp2		Exp1	
		F	L	F	L	F	L	F	L	F	L
Session	1	58	100	100	58	85	56	62	92	83	100
	2	30	100	100	64	73	83	58	94	100	50
	3	80	92	100	83	29	83	70	100	100	25
	4	75	90	73	92	40	50	86	100	100	20
	5	80	91					60	100		
	6	90	91					60	100		
Average		82.41		83.84		62.26		83.33		72.41	

Table D.12. System performance, CR_2/CE_2 (%) for subjects F1, F3 and F4 using Approach 2.

Subject		F1									
		Exp1		Exp2		Exp3		Exp4		Exp5	
		F	L	F	L	F	L	F	L	F	L
Session	1	30/0	80/0	60/0	90/0	70/0	60/0	100/0	60/0	90/0	70/0
	2	50/10	70/10	50/0	80/0	90/0	30/0	100/0	60/0	67/8	70/0
	3	40/0	90/0	40/10	90/0	80/0	60/0	100/0	60/0	88/0	88/3
	4	50/0	90/0	50/0	60/0	60/0	70/0	100/0	40/0	77/0	60/10
	5	10/0	100/0	40/10	90/0	60/0	90/0	100/0	40/10		
	6	40/0	100/0	70/0	70/10	70/0	90/0	100/0	30/0		
	7	50/0	100/0	60/0	70/0	60/0	100/0				
	8	20/10	90/0	70/0	70/0	80/0	100/0				
	9	30/40	90/0								
Average		62.8/4.4		66.3/1.9		73.1/0.0		74.2/0.8		80.3/1.7	

Subject		F1				F3				F4	
		Exp6		Exp7		Exp1		Exp2		Exp1	
		F	L	F	L	F	L	F	L	F	L
Session	1	42/0	100/0	93/0	42/8	69/0	44/33	54/15	92/0	83/17	90/0
	2	20/40	100/0	83/0	45/0	66/27	75/8	33/25	94/0	100/0	50/40
	3	20/7	75/0	100/0	50/8	14/57	67/8	40/20	100/0	100/0	8/58
	4	42/0	90/0	67/13	67/0	30/20	50/33	64/7	91/0	100/0	20/80
	5	60/0	64/0					40/20	100/0		
	6	60/0	33/0					50/20	91/0		
Average		60.71/3.57		68.69/4.04		57.89/24.53		73.33/8.00		68.96/23.76	

Table D.13. Comparison of the classification error, CE_2 (%) for subjects F1, F3 and F4 using Approach 1 and Approach 2.

Subject		F1									
		Exp1		Exp2		Exp3		Exp4		Exp5	
		A1	A2	A1	A2	A1	A2	A1	A2	A1	A2
Session	1	15	0	5	0	10	0	0	0	0	0
	2	30	10	10	0	10	0	10	0	27	5
	3	10	0	15	5	0	0	5	0	2	3
	4	20	0	25	0	5	0	0	0	0	5
	5	15	0	10	5	15	0	10	0		
	6	5	0	5	5	5	0	15	0		
	7	15	0	10	0	5	0				
	8	40	5	0	0	0	0				
	9	30	20								
Average		**20.0**	**4.4**	**10.0**	**1.9**	**6.3**	**0.0**	**6.7**	**0.8**	**5.65**	**1.7**

Subject		F1				F3				F4	
		Exp6		Exp7		Exp1		Exp2		Exp1	
		A1	A2	A1	A2	A1	A2	A1	A2	A1	A2
Session	1	20.0	0.0	19.2	3.8	29.5	16.5	23.0	7.5	8.3	8.5
	2	29.2	16.7	17.4	0.0	22.0	17.5	27.5	10.3	25	20.0
	3	14.8	3.7	8.7	4.2	44.0	32.5	11.1	7.4	37.5	29.0
	4	18.2	0.0	18.5	7.4	55.0	26.5	7.8	3.9	40.0	40.0
	5	13.6	0.0					18.2	9.1		
	6	9.1	0.0					18.2	9.5		
Average		**17.59**	**3.57**	**16.16**	**4.04**	**37.74**	**24.50**	**16.67**	**8.00**	**27.59**	**23.76**

Table D.14. System performance, CR_2 (%) for subjects F1, F2, F3, F5 and M1 using Approach 1.

		F1				F2		F3		F5	
		Exp8		Exp9		Exp1		Exp3		Exp1	
		F	L	F	L	F	L	F	L	F	L
Session	1	80	55	90	80	10	100	100	90	90	40
	2			100	100	10	100			90	70
	3			100	100	10	100			60	100
	4			100	88	40	70				
	5					10	90				
Average		**67.5**		**95.1**		**54.0**		**95.0**		**75.0**	

		M1							
		Exp1		Exp2		Exp3		Exp4	
		F	L	F	L	F	L	F	L
Session	1	90	100	80	100	82	91	100	85
	2	80	80	60	70	90	20		
	3	100	60			40	100		
	4	30	100			45	100		
	5					100	36		
	6					67	100		
Average		**80.0**		**77.5**		**71.9**		**92.5**	

Table D.15. System performance CR_2/CE_2(%) for subjects F1, F2, F3, F5 and M1 using Approach 2.

		F1				F2		F3		F5	
		Exp8		Exp9		Exp1		Exp3		Exp1	
		F	L	F	L	F	L	F	L	F	L
Session	1	65/5	45/15	70/0	50/0	0/80	100/0	100/0	30/10	90/10	40/40
	2			91/0	64/0	0/90	90/0			90/0	40/30
	3			85/0	75/0	10/90	100/0			30/0	90/0
	4			71/0	65/0	20/40	50/10				
	5					10/80	80/10				
Average		**55.0/10.0**		**71.3/0.0**		**46/40**		**61.5/5.0**		**63.3/13.3**	

		M1							
		Exp1		Exp2		Exp3		Exp4	
		F	L	F	L	F	L	F	L
Session	1	60/10	80/0	20/20	90/0	64/0	91/9	70/0	69/8
	2	70/0	60/0	60/40	50/10	90/0	10/60		
	3	60/0	60/0			0/20	80/0		
	4	0/50	100/0			18/36	90/0		
	5					100/0	0/45		
	6					33/29	90/0		
Average		**61.3/7.5**		**55.0/17.5**		**53.3/17.8**		**69.5/4.0**	

Table D.16. Comparison of the classification error, CE_2 (%) for subjects F1, F2, F3, F5 and M1 using Approach 1 and Approach 2.

		F1				F2		F3		F5	
		Exp8		Exp9		Exp1		Exp3		Exp1	
		A1	A2	A1	A2	A1	A2	A1	A2	A1	A2
Session	1	40	10	15	0	45	40	5	5	35	25
	2			0	0	45	45			20	15
	3			0	0	45	45			20	0
	4			6	0	50	25				
	5					45	45				
Average		**32.5**	**15.0**	**5.3**	**0.0**	**46.0**	**44.0**	**5.0**	**5.0**	**25.0**	**13.3**

		M1							
		Exp1		Exp2		Exp3		Exp4	
		A1	A2	A1	A2	A1	A2	A1	A2
Session	1	5	5	10	10	14	45	7.5	4.0
	2	20	0	35	25	45	30		
	3	20	0			30	10		
	4	35	25			28	18		
	5					32	23		
	6					17	15		
Average		**20.0**	**7.5**	**22.5**	**17.5**	**28.1**	**17.8**	**7.5**	**4.0**

Table D.17. Interpretation of the results in Table D.14 (Approach 1).

		M1											
		Exp1			Exp2			Exp3			Exp4		
		TP	FN	FP	TP	FN	FP	TP	FN	FP	TP	FN	FP
Session	1	90	10	0	80	20	0	82	18	9	100	0	15
	2	80	20	20	60	40	30	90	10	80			
	3	100	0	40				40	60	0			
	4	30	70	0				45	55	0			
	5							100	0	64			
	6							67	33	0			
Average		**75.0**	**25.0**	**15.0**	**70.0**	**30.0**	**15.0**	**70.7**	**29.3**	**25.5**	**100.0**	**0.0**	**15.0**

		F1						F3		
		Exp8			Exp9			Exp3		
		TP	FN	FP	TP	FN	FP	TP	FN	FP
Session	1	80	20	45	90	10	20	100	0	10
	2				100	0	0			
	3				100	0	0			
	4				100	0	12			
	5									
Average		**80.0**	**20.0**	**45.0**	**97.5**	**2.5**	**8.0**	**100.0**	**0.0**	**10.0**

Table D.18. Interpretation of the results in Table D.15 (Approach 2).

		M1											
		Exp1			Exp2			Exp3			Exp4		
		TP	FN	FP	TP	FN	FP	TP	FN	FP	TP	FN	FP
Session	1	60	40	0	20	80	0	64	36	9	70	30	8
	2	70	30	0	60	40	10	90	10	60			
	3	60	40	0				0	100	0			
	4	0	100	0				18	82	0			
	5							100	0	45			
	6							33	67	0			
Average		**47.5**	**52.5**	**0.0**	**40.0**	**60.0**	**5.0**	**50.8**	**49.2**	**19.0**	**70.0**	**30.0**	**8.0**

		F1						F3		
		Exp8			Exp9			Exp3		
		TP	FN	FP	TP	FN	FP	TP	FN	FP
Session	1	65	35	15	70	30	0	100	0	10
	2				91	9	0			
	3				85	15	0			
	4				71	29	0			
	5									
Average		**65.0**	**35.0**	**15.0**	**79.3**	**20.3**	**0.0**	**100.0**	**0.0**	**10.0**

Table D.19. System performance when the subjects were resting (2 minutes) to find IM1.

	F1		M1		F3
	Exp8	**Exp9**	**Exp2**	**Exp3**	**Exp3**
T_{up}	0.5068	0.9157	0.7343	0.6638	0.8218
T_{low}	-0.4103	-0.6505	-0.5906	-0.6925	-0.9349
No of samples classified as LEFT	74	66	87	86	91
No of samples classified as FOOT	25	21	7	23	7
Averaged LDA_{output}	-0.8378	-0.8782	-2.1718	-4.1392	-2.1726
Bias Class (IM2)	LEFT	LEFT	LEFT	LEFT	LEFT
IM1	FOOT	FOOT	FOOT	FOOT	FOOT

Table D.20. System performance when subject F1 was resting (2 minutes) to find IM1 (using the BCI Version 1).

	F1			
	Exp1	**Exp1**	**Exp5**	**Exp7**
T_{up}	2.1278	2.1278	1.0149	0.7214
T_{low}	-1.5809	-1.5809	-0.8676	-0.7459
No of samples classified as LEFT	100	94	91	68
No of samples classified as FOOT	14	14	9	19
Averaged LDA_{output}	-6.96	-5.7454	-2.6839	-1.1971
Bias Class (IM2)	LEFT	LEFT	LEFT	LEFT
IM1	FOOT	FOOT	FOOT	FOOT

Table D.21. Online performance of subjects F1, F3 and M1 using test sequence 1 and 2.

Parameter	Subject			
	F1		F3	
	Exp8 (1)	**Exp9 (2)**	**Exp3a (1)**	**Exp3b (1)**
Bias Class	LEFT	LEFT	LEFT	LEFT
T_c	8m 10s	10m 20s	17m	9m 35s
T_S	3m 45s	4m 20s	4m 30s	4m
T_{NA}	4m 25s	6m	12m 30s	5m 35s
TP	34	34	48	33
FN	11	18	6	15
FP	0	3	32	5
IA	12	12	12	12
UIA	0	0	10	0
FA	5	8	4	3
FP/min	0.00	0.50	2.56	0.90
UIA/min	0.00	0.00	0.80	0.00
ITR	2.06	1.50	0.82	1.66
Accuracy	88.74%	83.06%	81.38%	86.25%

Parameter	Subject		
	M1		
	Exp2a (1)	**Exp2b (1)**	**Exp4 (2)**
Bias Class	LEFT	LEFT	LEFT
T_c	16m	15m 5s	9m 15s
T_S	8m 10s	8m 30s	3m 20s
T_{NA}	7m 50s	6m 35s	5m 55s
TP	41	40	32
FN	57	62	8
FP	0	4	9
IA	12	12	12
UIA	0	1	0
FA	30	56	0
FP/min	0	0.6076	1.52
UIA/min	0.00	0.15	0.00
ITR	0.88	0.94	1.73
Accuracy	70.33%	63.54%	84.68%

Note: The number in the bracket in Table D.21 denotes the test sequence used in the experiment.

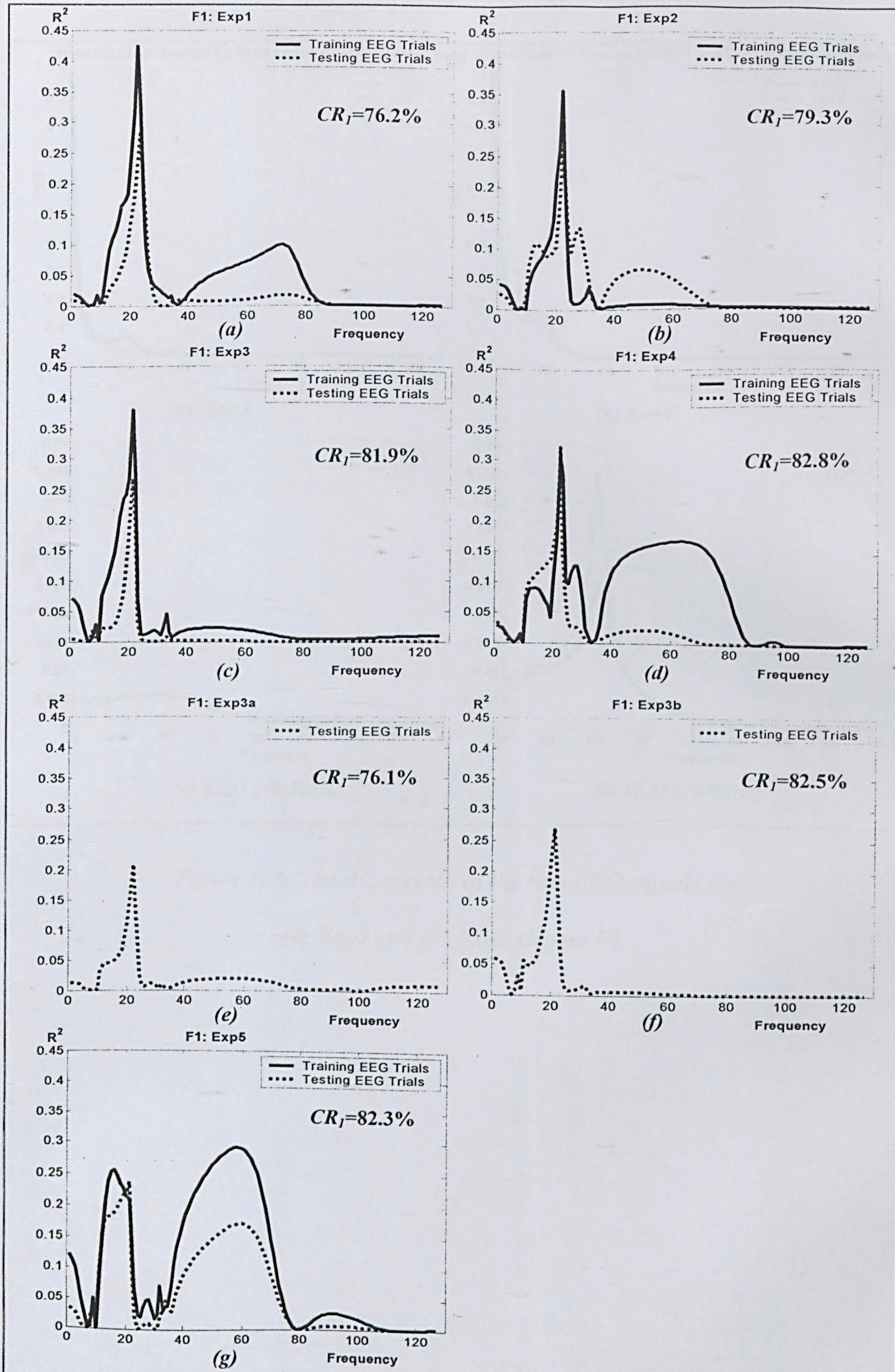
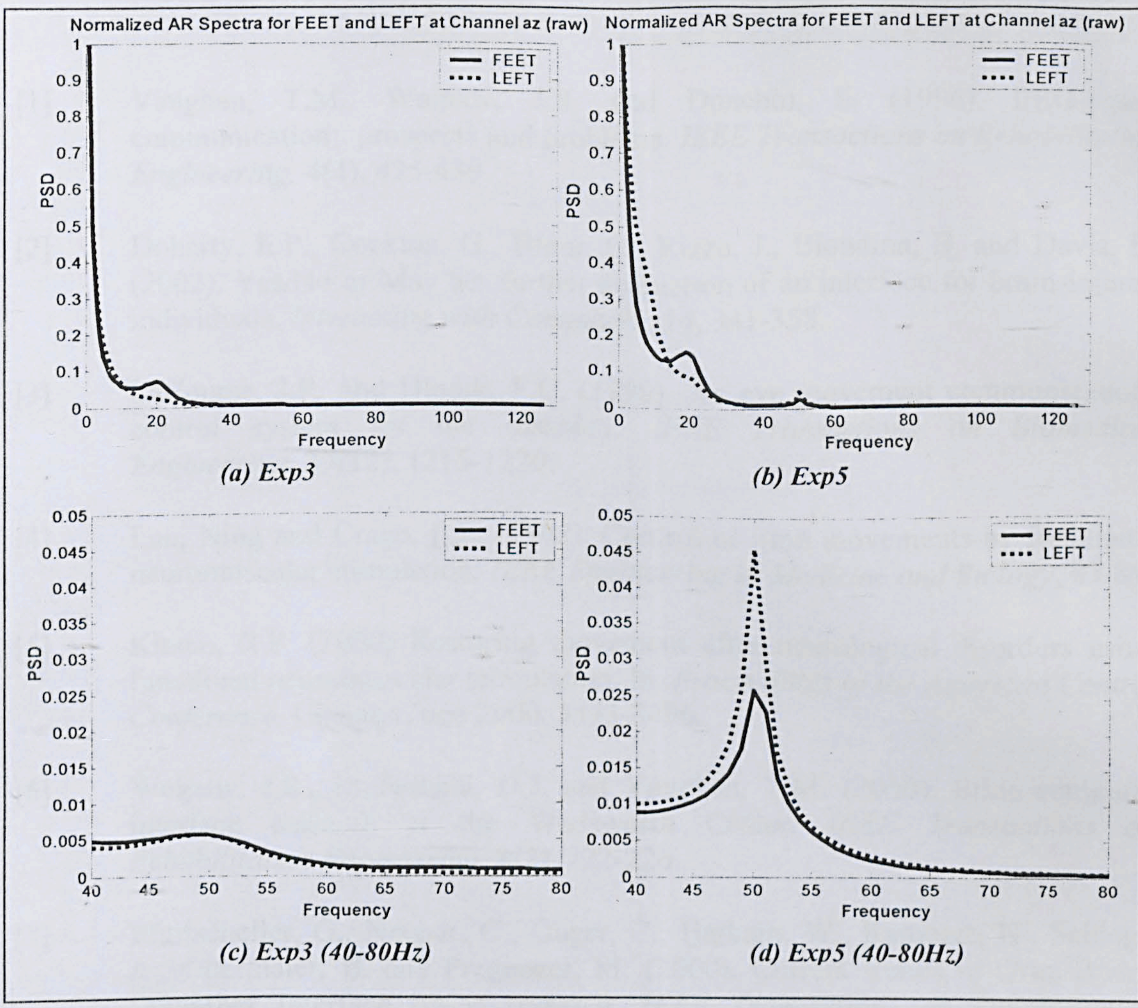


Figure D.5. The R^2 spectra of the training (classifier set-up phase) and the testing (subject-training phase) EEG trials in Exp1-Exp5 for subject F1.



(a) Exp3 *(b) Exp5*

(c) Exp3 (40-80Hz) *(d) Exp5 (40-80Hz)*

Figure D.6. The AR spectra of the raw EEG signals for

(a) Exp3 and (b) Exp5 subject F1.

REFERENCES

[1] Vaughan, T.M., Wolpaw, J.R. and Donchin, E. (1996). EEG-based communication: prospects and problems. *IEEE Transactions on Rehabilitation Engineering,* **4(4)**, 425-430.

[2] Doherty, E.P., Cockton, G., Bloor, C., Rizzo, J., Blondina, B. and Davis, B. (2002). Yes/No or May be- further evaluation of an interface for brain-injured individuals. *Interacting with Computers*, **14**, 341-358.

[3] LaCourse, J.R. and Hludik, F.C. (1990). An eye movement communication-control system for the disabled. *IEEE Transactions on Biomedical Engineering*, **37(12)**, 1215-1220.

[4] Lan, Ning and Crago, P.E. (1992). Control of limb movements by functional neuromuscular stimulation. *IEEE Engineering in Medicine and Biology*, 83-84.

[5] Kirsch, R.F. (2000) Restoring movement after neurological disorders using functional neuromuscular stimulation. In: *Proceedings of the American Control Conference.* Chicago June 2000, 3493-3496.

[6] Wolpaw, J.R., McFarland, D.J. and Vaughan, T.M. (2000). Brain-computer interface research at the Wadsworth Center. *IEEE Transactions on Rehabilitation Engineering,* **8(2)**, 222-226.

[7] Pfurtscheller, G., Neuper, C., Guger, C., Harkam, W., Ramoser, H., Schlogl, A., Obermaier, B. and Pregenzer, M. (2000). Current trends in Graz Brain-Computer Interface (BCI) research. *IEEE Transactions on Rehabilitation Engineering*, **8(2)**, 216-219.

[8] Pfurtscheller, G. and Neuper, C. (2001). Motor imagery and direct brain-computer communication. In: *Proceedings of the IEEE,* **89(7)**, 1123-1134.

[9] Scherer, R., Muller, G.R., Neuper, C., Graimann, B., and Pfurtscheller, G. (2004): An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate. *IEEE Transactions on Biomedical Engineering*, **51(6)**, 979-1307.

[10] Hinterberger, T., Mellinger, J. and Birbaumer, N. (2003). The Thought Translation Device: structure of a multimodal brain-computer communication system. In: *Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering*. Italy 20-22 March 2003, 603-606.

[11] Wolpaw, J.R., Birbaumer, N., Mcfarland, D.J., Pfurtscheller, G. and Vaughan, T.M. (2002). Brain-computer interface for communication and control. *Clinical Neurophysiology*, **113**, 767-791.

[12] Cheng, M., Gao, X.R., Gao, S.K. and Xu, D.F. (2002). Design and implementation of a brain-computer interface with high transfer rate. *IEEE Transactions on Biomedical Engineering,* **49(10)**, 1181-1186.

[13] Gao, X.R., Xu, D.F., Cheng, M. and Gao, S.K. (2003) A BCI-based environmental controller for motion-disabled. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* **11(2)**, 137-140.

[14] Middendorf, M., McMillan, G., Calhoun, G. and Jones, K.S. (2000). Brain-computer interfaces based on the steady-state visual evoked response. *IEEE Transactions on Rehabilitation Engineering*, **8(2)**, 211-214.

[15] Jones, K.S., Middendorf, M., McMillan, G.R., Calhoun, G. and Warm, J. (2003). Comparing mouse and steady-state visual evoked response-based control. *Interacting with Computers*, **15**, 603-621.

[16] Farwell, L.A. and Donchin, E. (1988) Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology*, **70(6)**, 510-523.

[17] Donchin, E., Spencer, K.M. and Wijesinge, R. (2000). The mental prosthesis: assessing the speed of a P300-based brain computer interface. *IEEE Transactions on Rehabilitation Engineering*. **8(2)**, 174-179.

[18] Hinterberger, T., Baier, G., Mellinger, J. and Birbaumer, N. (2004). Auditory feedback of human EEG for direct brain-computer communication. In: *Proceedings of ICAD 04-Tenth Meeting of the International Conference on Auditory Display*. Sydney, Australia, 6-9 July 2004.

[19] Birbaumer, N., Hinterberger, T., Karim, A.A., Kubler, A., Neumann, N. and Veit, R. (2004). Brain-computer communication using self-control of slow cortical potentials (SCP). In: *Proceedings of the 2nd International BCI Workshop and Training Course 2004.* Graz 17-18 September 2004, 1-4.

[20] Lauer, R.T., Peckham, P.H. and Kilgore, K.L. (1999). EEG-based control of a hand grasp neuroprosthesis. *Neuroreport*, **10**, 1767-1771.

[21] Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N. and Wolpaw, J.R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on Biomedical Engineering*, **51(6)**, 1034-1042.

[22] Birch, G.E., Mason, S.G. and Borisoff, J.F. (2003). Current trends in Brain-Computer Interface research at the Neil Square Foundation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 123-126.

[23] Millan, J.d.R., Renkens, F., Mourino, J. and Gerstner, W. (2004). Brain-actuated interaction. *Artificial Intelligent*, **159**, 241-259.

[24] Pfurtscheller, G., Neuper, C., Muller, G.R., Obermaier, B., Krausz, G., Schlogl, A., Scherer, R., Graimann, B., Keinrath, C., Skliris, D., Wortz, M., Supp, G. and Schrank, C. (2003) Graz-BCI: state of the art and clinical applications. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 177-180.

[25] Krepki, R., Blankertz, B., Curio, G., and Müller, K.R. (2003). The Berlin Brain-Computer Interface (BBCI): towards a new communication channel for online control of multimedia applications and computer games. In: *9th International Conference on Distributed Multimedia Systems (DMS'03)*. 237-244.

[26] Penny W.D., Robert, S.J., Curran, E.A. and Stokes, M.J. (2000). EEG-based communication: A pattern recognition approach. *IEEE Transactions on Rehabilitation Engineering*, **8(2)**, 214-215.

[27] Anderson, C.W., Stolz, E.A. and Shamsunder, S. (1998). Multivariate autoregressive models for classification of spontaneous EEG signals during mental tasks. *IEEE Transactions on Biomedical Engineering*, **45(3)**, 277-285.

[28] Sutter, E.E. (1992). The Brain Response Interface: communication through visually induced electrical brain responses. *J. Microcomputer Appl.*, **15**, 31-45.

[29] Levine, S.P., Huggins, J.E., BeMent, S.L., Kushwaha, R.K., Schuh, L.A., Rohde, M.M., Passaro, E.A., Ross, D.A., Elisevich, K.V. and Smith, B.J. (2000) A direct brain interface based on event-related potentials. *IEEE Transactions on Rehabilitation Engineering*, **8(2)**, 180-185.

[30] Schwartz, A.B., Taylow, D.M. and Tillery, S.I.H. (2001). Extraction algorithms for cortical control of arm prosthetics. *Cur. Opin. Neurobio.*, **11**, 701-707.

[31] Taylor, D.M., Tillery, S.I. and Schwartz, A.B. (2002). Direct cortical control of 3D neuroprosthetic devices. *Science*, **296(5574)**, 1829-1832.

[32] Black, M.J., Bienenstock, E., Donoghue, J.P., Serruya, M., Wu, W., Gao, Y.. (2003). Connecting brains with machines: The neural control of 2D cursor movement. In: *1st International IEEE/EMBS Conference on Neural Engineering.* Italy March 20-22, 2003. 580-583.

[33] Kennedy, P.R., Bakay, R.A.E., Moore, M.M., Adams, K. and Goldwaithe, J. (2000). Direct control of a computer from the human central nervous system. *IEEE Transactions on Rehabilitation Engineering*, **8(2)**, 198-202.

[34] Pfurtscheller, G., Neuper, C., Schlogl, A. and Lugger, K. (1998). Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. *IEEE Transactions on Rehabilitation Engineering*, **6(3)**, 316-325.

[35] Guger, C., Schlogl, A., Neuper, C., Walterspacher, D., Strein, T. and Pfurtscheller, G. (2001). Rapid prototyping of an EEG-based brain-computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **9(1)**, 49-58.

[36] Wolpaw, J.R., Ramoser, H., McFarland, D.J. and Pfurtscheller, G. (1998). EEG-based communication: Improved accuracy by response verification. *IEEE Transactions on Rehabilitation Engineering*, **6(3)**, 326-333.

[37] Miner, L.A., McFarland, D.J. and Wolpaw, J.R. (1998) Answering questions with an electroencephalogram-based brain-computer interface. *Arch Phy Med Rehabil.*, **79**, 1029-1033.

[38] Blankertz, B., Curio, G. and Muller, K.R. (2002). Classifying single trial EEG: towards brai computer interfacing. *Advances in Neural Information Processing Systems (NIPS 01),* eds. Diettrich, G., Becker, S., Ghahramani, Z.. Cambridge, MA: MIT Press, **14**, 157-164.

[39] Birbaumer, N. and Kubler, A. (2000). The thought translation device (TTD) for completely paralyzed patients. *IEEE Transactions on Rehabilitation Engineering,* **8(2)**, 190-193.

[40] Hinterberger, T., Kubler, A., Kaiser, J., Neumann, N. and Birbaumer, N. (2003). A brain-computer interface (BCI) for the locked-in: comparison of different EEG classifications for the thought translation device. *Clinical Neurophysiology*, **114**, 416-425.

[41] Mason, S.G. and Birch, G.E. (2000). A brain-controlled switch for asynchronous control applications. *IEEE Transactions on Biomedical Engineering,* **47(10)**, 1297-1307.

[42] Birch, G.E., Bozorgzadeh, Z. and Mason, S.G. (2002). Initial online evaluations of the LF-ASD brain-computer interface with able-bodied and spinal cord subjects using imagined voluntary motor potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **10(4)**, 219-224.

[43] Millan, J.d.R and Mourino, J. (2003). Asynchronous BCI and local neural classifiers: an overview of the adaptable brain interface project. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* **11(2)**, 159-161.

[44] Borisoff, J.F., Mason, S.G., Bashashati, A. and Birch, G.E. (2004). Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch. *IEEE Transactions on Biomedical Engineering,* **51(6)**, 985-992.

[45] McFarland, D.J., McCane, L.M. and Wolpaw, J.R. (1998). EEG-based communication and control: short term role of feedback. *IEEE Transactions on Rehabilitation Engineering*, **6(1)**, 7-11.

[46] McFarland, D.J., Sarnacki, W.A. and Wolpaw, J.R. (2003). Brain-computer interface operation: optimizing information transfer rates. *Biological Psychology*, **63**, 237-251.

[47] Birbaumer, N., Hinterberger, T., Kubler, A. and Neumann, N. (2003). The Thought-Translation Device (TTD): neurobehavioral mechanisms and clinical outcome. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 120-123.

[48] Schroder, M., Bogdan, M. Rossenstiel, W., Hinterberger, T. and Birbaumer, N. (2003). Automated EEG feature selection for brain-computer interfaces. In: *Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering.* Capri Island, Italy, 20-22 March 2003, 626-629.

[49] Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., J., Taub, Kotchoubey, B., Kubler, A. and Perelmouter,.J. (1999). A spelling device for the paralyzed. *Nature*, **398**, 297-298.

[50] Guger, C., Ramoser, H. and Pfurtscheller, G. (2000). Real-time EEG analysis with subject-specific spatial patterns for a brain-computer interface (BCI). *IEEE Transactions on Rehabilitation Engineering*, **8(4)**, 447-456.

[51] Neuper, C., Muller, G.R., Kubler, A., Birbaumer, N. and Pfurtscheller, G. (2003). Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment. *Clinical Neurophysiology.* **114**, 399-409.

[52] Pfurtscheller, G., Guger, C., Muller, G., Krausz, G. and Neuper , C. (2000). Brain oscillations control hand orthosis in a tetraplegic. *Neuroscience Letters*, **292**, 211-214.

[53] Bayliss, Jessica D. (2003). Use of the Evoked Potential P3 Component for Control in a Virtual Apartment. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 113-116.

[54] Sun, M.S., Mickle, M., Liang, W., Liu, Q. and Sclabassi, R.J. (2003). Data communication between brain implants and computer. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 189-191.

[55] Neat, G.W., McFarland, D.J., Forneris, C.A. and Wolpaw, J.R. (1990). EEG-based brain-to-computer communication: system description. In: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* **12(5)**, 2298-2300.

[56] Wolpaw, J.R., McFarland, D.J. and Cacace, A.T. (1986). Preliminary studies for a direct brain-to-computer interface. *IBM Technical Symposium: Projects for persons with Disabilities*, 11-20.

[57] Curran, E.A. and Stokes, M.J. (2003). Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems. *Brain and Cognition,* **51**, 326-336.

[58] Wolpaw, J.R., McFarland, D.J., Neat, G.W. and Forneris, C.A. (1991). An EEG-based brain-computer interface for cursor control. *Electroencephalography and Clinical Neurophysiology*, **78**, 252-259.

[59] Pfurtscheller, G. (2004) Importance of motor imagery and of feedback observation of a moving object in BCI research. In: *Proceedings of the 2nd International BCI Workshop and Training Course 2004.* Graz 17-18 September 2004, 23-28.

[60] Bozorgzadeh, Z., Birch, G. and Mason, S.G. (2000). The LF-ASD brain computer interface: online identification of imagined finger flexions in the spontaneous EEG of able-bodied subjects. In: *Proceedings of the ICASSP 2000 (IEEE).* Istanbul, Turkey July 2000, 4, 2385-2388.

[61] Guger, C., Edlinger, G., Harkam, W., Niedermayer, I. and Pfurtscheller, G. (2003). How many people are able to operate an EEG-Based brain-computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 143-147.

[62] Pfurtscheller, G., Kalcher, J., Neuper, C., Flotzinger, D. and Pregenzer, M. (1996). Online EEG classification during externally-paced hand movements using a neural network-based classifier. *Electroencephalography and Clinical Neurophtsiology*, **99**, 416-425.

[63] Peter, B.O., Pfurtscheller, G. and Flyvbjerg. (2001). Automatic differentiation of multichannel EEG signals. *IEEE Transactions on Biomedical Engineering*, **48(1)**, 111-116.

[64] Schlögl, A., Lugger, K. And Pfurtscheller, G. (1997). Using adaptive autoregressive parameterrrs for a brain-computer interface experiment. In: *Proceedings-19th International Conference- IEEE/EMBS.* Chicago 30 October- 2 November 1997, 1533-1535.

[65] Vidaurre, C., Schlögl, A., Cabeza, R. And Pfurtscheller, G. (2004). About adaptive classifiers for brain computer interfaces. In: *Proceedings of the 2nd International BCI Workshop and Training Course 2004.* Graz 17-18 September 2004, 85-86.

[66] Lal, T.N., Schroder, M., Hinterberger, T., Weston, J., Bogdan, M., Birbaumer, N. and Scholkopf, B. (2004). Support vector channel selection in BCI. *IEEE Transactions on Biomedical Engineering*, **51(6)**, 1003-1010.

[67] Dornhege, G., Blankertz, B., Curio, G. and Muller, K.R. (2004). Combining Features for BCI. In Becker, S., Thrun, S. and Obermayer, K. editors, *Advances in Neural Information Processing Systems 15*, Cambridge, MA, 2003. MIT Press.

[68] Yu, Z., Mason, S.G. and Birch, G.E. (2002). Enhancing the performance of the LF-ASD brain-computer interface. In: *Proceedings of the Second Joint EMBS/BMES Conference.* Houston, Texas 23-28 October 2002, 2443-2444.

[69] Millan, J.d.R., Mourino, J., Cincotti, Febo, Varsta, M., Heikkonen, J., Topani, F., Marciani, M.G., Kaski, Kimmo and Babiloni, F. (2000) Neural Networks for robust classification of mental tasks. In: *Proceedings of the 22nd Annual EMBS International Conference.* Chicago 23-28 July 2000, 1380-1382.

[70] McFarland, D.J., McCane, L.M., David, S.V. and Wolpaw, J.R. (1997). Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology*, **103**, 386-394.

[71] Flotzinger, D., Pfurtscheller, G., Neuper, C., Mohl, W. and Berger, H. (1993). Classification of non-averaged EEG data by learning vector quantization and the impact of signal preprocessing. In: *Proceedings of the 15th Annual International Conference of the IEEE: Engineering in Medicine and Biology Society,* 263-264.

[72] Polak, M. and Kostov, A. (1998). Feature extraction in development of brain-computer interface: a case study. In: *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* **20(4)** 2058-2061.

[73] Fenwick, P.B.C., Mitchie, P., Dollimore, J. and Fenton, G.W. (1969). Application of the autoregressive model to EEG analysis. *Agressologie*, **10**, 553-564.

[74] Pfurtcheller, G. and Haring, G. (1972). The use of an EEG autoregressive model for the time-saving calculation of spectral power density distributions with a digital computer. *Electroencephalography Clinical Neurophysiology*, **33**, 113-115.

[75] Varsta, M., Heikkonen, J., Millan, J. dR. and Mourino, J. (2000). Evaluating the performance of three feature sets for brain-computer interfaces with an early stopping MLP committee. *ICPR 2000*, 2907-2910.

[76] Jansen, B., Bourne, J. and Ward, J. (1981). Autoregressive estimation of short segment spectra for computerized EEG analysis. *IEEE Transactions of Biomedical Engineering,* **5**, 630-638.

[77] Foster, M.J., McFarland, D.J. and Wolpaw, J.R. (1995). Improvement in EEG-based brain-computer communication by use of additional recording locations. In: *RESNA 95 Annual Conference*, 687-689.

[78] McFarland, D.J., Lefkowicz, A.T. and Wolpaw, J.R. (1996). Design and operation of an EEG-based brain-computer interface (BCI) with digital signal processing technology. *Behavioral Res. Methods, Instrum. and Comput.*, **29**, 337-345.

[79] Garrett, D., Peterson, D.A., Anderson, C.W. and Thaut, M. (2003). Comparison of linear, nonlinear and feature selection methods for EEG signal classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 141-144.

[80] Robert, S.J. and Penny, W.D. (2000). Real-time brain-computer interfacing: a preliminary study using Bayesian learning. *Medical and Biological Engineering and Computing,* **38(1)**, 56-61.

[81] Box, G.E.P. and Jenkins, G.M. (1969). *Time Series Analysis Forecasting and Control*, 1st edn. California: Holden-Day.

[82] Haykin, S. (2000). *Adaptive Filter Theory.* 4th Edn. USA: Prentice Hall.

[83] Schlögl, A., Müller, G., Neuper, C., Krausz, G., Graimann, G. and Pfurtscheller, G. (2001). Adaptive autoregressive parameters in BCI research. In: *NIPS 2001, Brain Computer Interface Workshop.* Whistler, Canada 7. Dec. 2001.

[84] Proakis, J.G. and Manolakis, D.G. (1996). *Digital Signal Processing: Principles, Algorithms, and Applications,* 3rd edn. USA: Prentice-Hall International.

[85] Graimann, B., Huggins, J.E., Livine, S.P. and Pfurtscheller, G. (2004). Toward a direct brain interface based on human subdural recordings and wavelet packet analysis. *IEEE Transactions on Biomedical Engineering*, **51(6)**, 954-962.

[86] Muller, K.R., Anderson, X.W. and Birch, G.E. (2003). Linear and nonlinear methods for brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 165-168.

[87] Blankertz, B., Dornhege, G., Schafer, C., Krepki, R., Kohlmorgen, J., Mullter, K.R., Kunzmann, V., Losch, F. and Curio, G. (2003). Boosting bit rates and error detection for the classification of fast-pace motor commands based on Proakis, J.G. and Manolakis, D.G. (1996). *Digital Signal Processing: Principles, Algorithms, and Applications,* 3rd edn. USA: Prentice-Hall International.single-trial EEG analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 127-131.

[88] Raudys, S. (2001). *Statistical and Neural Classifiers: An Integrated Approach to Design*. Great Britain:Springer.

[89] Cincotti, F., Mattia, D., Babiloni, C., Carducci, F., Salinari, S., Bianchi, L., Marciani, M.G. and Babiloni, F. (2003). The use of EEG Modifications due to motor imagery for brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11(2)**, 131-133.

[90] Phang, Y.M. and Goh, S.Y. (2004). A battery operated EEG amplifier. In: *3rd Technical Postgraduate Symposium 2004 (TECHPOS'04).* Kuala Lumpur 15-16 September 2004, TP04-BM-004, 16-18.

[91] Lim, E., Goh S.Y. and Taha, Z. (2004). Development of a real-time control system for a prosthestic hand. *3rd Technical Postgraduate Symposium 2004 (TECHPOS'04).* Kuala Lumpur 15-16 September 2004, TP04-BM-006, 25-27.

[92] Silva, F.L.D., and Niedermeyer, E. (1993). *Electroencephalography: Basic Principles, Clinical Applications and Related Fields,* 4th edn. USA: Lipponcott Williams & Wilkins.

[93] Mendenhall, W. and Sincich, T. (1995). *Statistics for Engineering and the Sciences*, 4th edn. USA: Prentice-Hall.

[94] Dawson-Saunders, B. and Trap, R.G. (1994). *Basic & Clinical Biostatiostics*, 2nd edn. USA: Appleton & Lange.

[95] Kleinbaum, D.G., Kupper, L.L., Muller, Keith E. and Nizam, A. (1998). *Applied Regression Analysis and Other Multivariate Methods,* 3rd edn. USA: Brooks/Cole Publishing Company.

[96] Sheikh, H., McFarland, D.J., Sarnacki, W.A. and Wolpaw, J.R. (2003). Electroencephalographic (EEG)-based communication: EEG control bersus system performance in humans. *Neuroscience Letters*, **345**, 89-92.

[97] Vaughan, T.M., Miner, L.A., McFarland, D.J. and Wolpaw, J.R. (1998). EEG-based communication: analysis of concurrent EMG activity. *Electroencephalography and Clinical Neurophysiology*, **107**, 428-433.

[98] Bell, B.M. and Percival, D.B. (1991). A two step burg algorithm. *IEEE Transactions On Signal Processing*, **19(1)**, 185-189.

[99] Ulrych, T.J. and Bishop, T.N. (1975). Maximum entropy spectral analysis and autoregressive decomposition. *Rev. Geophys. Space Phys.,* **13**, 183-200.

[100] Hayes, M. H. (1996). *Statistical Digital Signal Processing and Modeling*, 1st edn. New York: John Wiley & Sons.

[101] Waele, S.D. and Broersen, P.M.T. (2000). Spectral analysis of segmented data. *39th IEEE Conference on Decision and Control, December 2000 Sydney*, 189-190.

[102] Kay, S.M. and Marple, S.L. (1981). Spectrum analysis-a modern perspective. In: *Proc. IEEE*, **99**, 1380-1419.

[103] De Hoon, M.J.L., Van Der Hagen, T.H.J.J., Schoonewelle, H. and Van Dam, H. (1996). Why Yule-Walker should not be used for autoregressive modeling. *Annals of Nuclear Energy*, **23**, 1219-1228.

[104] Boersen P.M.T. (1997). The ABC of autoregressive order selection criteria. *Preprints Sysid'97 Conf., July 1998 Kitakyushu. Japan*, 231-236.

[105] Waele, S.D. and Broersen, P.M.T. (1997) The Burg algorithm for segments. *IEEE Transactions on Signal Processing,* **48(10)**, 2876-2879.

[106] Shiavi, R. (1999). *Introduction to Applied Statistical Signal Analysis*, 2nd edn. USA: Academic Press.

[107] Bianchi, A.M., Leocani, L., Mainardi, L.T., Comi, G. and Cerutti, S. (1998). Time-frequency analysis of event-related brain potentials. *20th International Conference of the IEEE Engineering in Medicine and Biology Society 1998*, **20(3)** 1486-1489.

[108] Poulos M, Rangoussi M, Chrissicopoulos V, Evangelou A. (1999). Person identification based on parametric processing on the EEG. *Proceedings of the Sixth International Conference on Electronics, Circuits and Systems (ICECS99). Institute of Electrical and Electronics Engineers, Pafos, Cyprus 1999*, **1**, 283-286.

[109] Paui, J.S., Tong, S., Sherman, D., Bezerianos, A. and Thakor, N.V. (2001). On the application of model based distance metrics of signals for detection of brain injury, *Statistical Signal Processing, Proceedings of the 11^th IEEE Signal Processing Workshop,* 257-260.

[110] Pfurtscheller, G., Zalaudek, K. and Neuper, C. (1998). Event-related beta synchronization after writst, finger and thumb movement. *Electroencephalography and Clinical Neurophysiology,* **109**, 154-160.

[111] Pfurtscheller, G. (1981). Central beta rhythm during sensory motor activities in man. *Electroenceph. Clin. Neurophysiol.*, **51**, 253-264.

[112] Pfurtscheller, G. (1989). Functional topography during sensorimotor activation studied with event-related desynchronization mapping. *J. Clin. Neurophysiol.*, **6(1)**, 75-84.

[113] Johnson, T.A. and Wichen, D.W. (2002). *Applied Multivariate Statistical Analysis, 5^th edn*. USA: Pearson Education International.