EFFECT OF MINDFULNESS MEDITATION ON BRAIN-COMPUTER INTERFACE PERFORMANCE

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NOVEMBER 2014

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By

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A thesis submitted to the Department of
Mechatronics and Biomedical Engineering,
Lee Kong Chian Faculty of Engineering and Science,
Universiti Tunku Abdul Rahman,
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Engineering
November 2014

DEDICATION

To my beloved family and husband

ABSTRACT

Electroencephalogram based Brain-Computer Interfaces (BCIs) enable stroke and motor neuron disease patients to communicate and control devices. Mindfulness meditation has been claimed to enhance metacognitive regulation. The current study explores whether mindfulness meditation training can thus improve the performance of BCI users. To eliminate the possibility of expectation of improvement influencing the results, we introduced a music training condition. A norming study found that both meditation and music interventions elicited clear expectations for improvement on the BCI task, with the strength of expectation being closely matched. In the main 12-week intervention study, seventy-six healthy volunteers were randomly assigned to three groups: a meditation training group; a music training group; and a no-treatment control group. The mindfulness meditation training group obtained a significantly higher BCI accuracy compared to both the music training and no-treatment control groups after the intervention, indicating effects of meditation above and beyond expectancy effects.

ACKNOWLEDGEMENT

I was very lucky to have so many nice people around me along the journey of my postgraduate study. I could never complete my study without their assistance, support, and efforts.

First and foremost, I would like to express my deepest gratitude to my supervisor, Prof. Goh Sing Yau, for his guidance and support. I have been greatly inspired by his enthusiasm in brain science research and motivated by his philosophy of life. During the most difficult times, he has provided me not only with valuable advice, but also encouragement and freedom that I needed to move on.

It was my great honour to work with Prof. Zoltan Dienes from University of Sussex. I am grateful and indebted for his expertise, guidance, and patience extended to me in explaining the Bayesian statistics, answering all my dummy questions, and reading my manuscript.

I would like to thank my collaborator Ashok Jansari, my seniors Siew Cheok, Einly, Xin Yi, and Yoke Mun, my teammates Danny, Justin, Vincent, Siew Ying, Siow Cheng, Yih Miin, and Yin Qing for their valuable inputs and support at different stages of my research. I am also thankful to Francis Lau, Chun Yong, and Uncle Ho for their expertise and technical supports.

I would like to take this opportunity to thank UTAR for providing me a scholarship and a laboratory for running the experiments. Thanks also go to the administrative staff, laboratory staff, and colleagues who helped and supported me.

Last but not least, I would like to thank all who have volunteered to participate in the study.

APPROVAL SHEET

This thesis entitled "**EFFECT OF MINDFULNESS MEDITATION ON BRAIN-COMPUTER INTERFACE PERFORMANCE"** was prepared by TAN LEE FAN and submitted as partial fulfillment of the requirements for the degree of Doctor of Philosophy in Engineering at Universiti Tunku Abdul Rahman.

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SUBMISSION OF THESIS

It is hereby certified that **TAN LEE FAN** (ID No: **07UED02915**) has completed this thesis entitled "**EFFECT OF MINDFULNESS MEDITATION ON BRAIN-COMPUTER INTERFACE PERFORMANCE**" under the supervision of **Prof. Dato' Ir. Dr. GOH SING YAU** (Supervisor) from the Department of Mechanical and Material Engineering, Lee Kong Chian Faculty of Engineering and Science.

I understand that University will upload softcopy of my thesis in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

Yours truly,

____
(TAN LEE FAN)

DECLARATION

I hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name ______________________________

Date _______________________________

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LIST OF ABBREVIATIONS

ANCOVA	one-way analysis of covariance
ANOVA	one-way analysis of variance
AR	autoregressive
BCI	brain-computer interface
EEG	electroencephalogram
GUI	graphical user interface
LDA	linear discriminant analysis
SE	standard error

CHAPTER 1

INTRODUCTION

A Brain-Computer Interface (BCI) captures the electrical activities of the brain and translates them into commands that can be understood by output devices. The BCI allows the users to control external devices without using their normal neuromuscular output pathways (Wolpaw et al., 2000). It therefore provides a new interaction channel to individuals who have little or no voluntary control over their bodies but yet retain a certain level of normal brain functions.

The term of “brain-computer interface” was first introduced in the work by Dr. Vidal in the early 1970s in which a human-computer interaction based on electroencephalogram (EEG) was proposed (Vidal, 1973). Over the past few decades, many BCI systems have been developed to provide various applications to the users. It is estimated that more than 100 million potential users around the world could benefit from the BCI technology, with the majority being stroke and motor neuron disease patients (Guger, 2008). Such individuals could use the BCI to communicate with others and to perform different daily tasks.

The BCI interprets the user’s intent through direct measures of brain activity, most commonly via EEG because the application of EEG electrodes on the scalp is non-invasive. The operation of the BCI is dependent on the effective interaction between the user who provides the input signals and the system that interprets the input signals (Wolpaw et al., 2000). Different techniques of temporal and spatial filtering (Dornhege et al., 2006) as well as signal processing algorithms (Bashashati et al., 2007) had been used in BCIs to improve the signal-to-noise ratio of the input signals. For the users, one of the biggest challenges is to produce consistent and reliable EEG patterns when they operate the BCIs. The brain signals as a measure of physiological responses are very much dependent on the ability of the individuals to regulate their mental states.

BCI research has focused primarily on the possible benefits to the disabled users. Any means of improving the effectiveness with which people can use BCI devices could dramatically improve their lives. In this context, a related question is whether people with mental training background and skills might control the BCI better. A candidate of mental training is mindfulness meditation because of its claimed ability to lead to better self-regulation (Cahn and Polich, 2006; Sedlmeier et al., 2012), though relatively few studies have compared its effects to an active control treatment of equivalent plausibility.

The aim of the present study is to investigate the effect of mindfulness meditation intervention on a group of BCI users, through a random-controlled design. The BCI performance of the meditators was compared to a no-treatment control group and an additional active control group (a group that underwent another type of mental training). To examine whether expectation could account for the effect of treatment, a survey on people's expectations towards mindfulness meditation and the active control treatment was conducted prior to the main BCI study. The overall study thus explored the use of mindfulness meditation in gaining better control of BCI devices, above and beyond expectation effects. It also addressed the theoretical issues concerning the nature of mindfulness meditation by way of exploring, for the first time, this possible practical benefit.

The rest of thesis is structured as follows:

Chapter 2 provides a literature review regarding the BCI, meditation, and the active control (musical training).

Chapter 3 emphasizes on the designs and operating principles of our present BCI system. The montage, experimental protocol, and processing method of the offline and the online BCI experiments are described. A BCI sequence test was developed for the purpose of the present study.

Chapter 4 describes the methodology of the randomized controlled trial study. It started with a questionnaire survey that measures the expectancy effect and followed by a randomized controlled BCI experiment that measures the effectiveness of mindfulness meditation on BCI performance. To perform the Bayesian statistical analysis, a computer program to calculate Bayes factor was created. The assumptions and algorithms used in the program are explained in this chapter.

Chapter 5 presents the results obtained from the statistical analyses using conventional non-significance hypothesis test and Bayesian approach. The results are discussed in Chapter 6.

Chapter 7 concludes the thesis with a summary of findings from the study. Some suggestions for future work are also proposed and discussed here.

CHAPTER 2

LITERATURE REVIEW

2.1 Brain-computer interface (BCI)

The term “brain-computer interface” was first used in the work of Dr. Vidal (Vidal, 1973) in which a human-computer interface that used brain signals was proposed. The BCI is defined as “a direct communication system that does not rely on the brain’s normal output pathways of peripheral nerves and muscles” (Wolpaw et al., 2000). In other words, a BCI depends solely on mental activity to enable a user to communicate and to control a device such as a motorized wheelchair. This technology is especially useful for individuals who are paralyzed or suffer from severe movement deficits. Other human-computer interface systems that utilized signals from muscle control (Chen et al., 2007) or eye movement (Lv et al., 2008) are available and easier to operate by users but such system may not be beneficial for patients with more severe motor disabilities, such as late-stage amyotrophic lateral sclerosis (ALS), severe cerebral palsy, and brainstem strokes (Daly and Wolpaw, 2008).

The BCIs can be categorized into two groups according to the placement of the sensors used to detect and acquire the brain signals: invasive BCIs and non-invasive BCIs. In invasive BCIs, electrodes are placed directly on the exposed surface of the brain or directly implanted into the brain tissue to capture electrical activity from the cerebral cortex (Kennedy et al., 2000; Leuthardt et al., 2004). These BCIs provide much better spatial resolution than the non-invasive one. However, some issues have been raised regarding their use such as biocompatibility of the implant, disruptive effects on the surrounding brain tissue, cost, difficulty and risk of the surgery, as well as the ethical concerns on the subjects (Wolpaw et al., 2006). For these reasons, non-invasive BCIs, are often preferred over the invasive BCIs. In a non-invasive manner, EEG electrodes are placed on the scalp to monitor electric brain activity. This is the most widely used method in BCIs.

All the BCI systems, regardless of the definitions, methods of acquiring input signals, and purposes of application, have the same major elements. Figure 2.1 shows a typical design of BCI systems. It comprises a data acquisition module that performs the recording, amplification, and digitization of the brain signals; a signal processing unit that completes all the processing including artifact rejection, filter, feature extraction, and classification of the data. After classification and a decision is made, an execute command is sent to the output device to perform the desired task. The output device could be simply a computer screen to present the user with a selection of targets or characters (Schalk et al., 2004), or a more advanced virtual reality environment (Leeb et al., 2007). The output device could also be a prosthesis hand (Muller-Putz and Pfurtscheller, 2008), a wheelchair (Tan et al., 2008), or a certain home appliance (Wang et al., 2006).

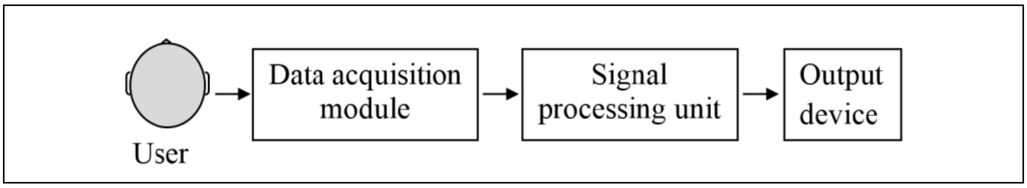


Figure 2.1 The typical components in a BCI system.

EEG from several kinds of mental activities can be used to operate a BCI system (Wolpaw et al., 2002), and they can be basically divided into evoked potential and spontaneous signals. Evoked potential are brain potentials that can be evoked by specific stimulus (e.g., visual evoke potential, P-300) while spontaneous EEG signals are those that occur during normal brain functions (e.g., sensorimotor rhythm, slow cortical potentials, non-motor cognitive tasks). Each type of input brain signal has its advantages and is used to fit into different BCI applications. For the BCI systems that use spontaneous EEG signals, the subjects have to be trained to control the system by developing an automated skill of controlling certain EEG components or performing certain mental tasks (in the present study, subjects perform motor imagery of left hand movement, right hand movement, as well as foot movement). Changes in EEG patterns, due to mu and beta rhythm desynchronization and synchronization, are distinguishable (Pfurtscheller and Lopes da Silva, 1999) and therefore can be used as input to the BCI system. Examples of successful motor imagery driven BCI systems are Graz (Pfurtscheller et al., 2003), Berlin (Blankertz et al., 2008), and Wadsworth (Jeffreys, 1961) BCIs.

As mentioned earlier, a BCI is a direct communication between two adaptive controllers, which are the computer and the user's brain. A successful operation of the BCI necessitates effective interaction between the user and the system itself (Wolpaw et al., 2000). One of the biggest challenges faced by BCI users is to produce consistent and reliable EEG patterns when they operate the BCIs and this is much dependent on the ability of the users to regulate their mental states. A number of factors could affect their EEG patterns. Unstable mental states due to anxiety, fatigue, frustration, or loss of concentration may cause inconsistent EEG patterns. Distraction during the experiment, for instance, caused by feedback presented by BCIs, can also modify the EEG and introduce noise to the system (Pfurtscheller and Neuper, 2001; Guger et al., 2003). Researchers have been trying to apply different signal processing techniques for BCIs in an attempt to improve the signal-to-noise ratio of the input signal (Bashashati et al., 2007; Tangermann et al., 2012). Other studies trained users to control their EEG patterns through extensive and resource demanding neuro-/biofeedback training (Neuper et al., 1999; Hwang et al., 2009). Although the efforts are useful, the processes are laborious and time consuming. Moreover, the processes, if conducted before actual use on a BCI, will cause fatigue on the subject and reduce the valuable remaining time of the subject for controlling the system.

I am not aware of any previous randomized controlled trial study in the field of BCI, except an earlier pilot study conducted by myself (Tan et al., 2009). BCI experiments are invariably laborious. The present study is an attempt to use a randomized controlled trial design to examine the effects of mindfulness meditation on the BCI performance among a group of meditation-naïve participants.

2.2 Mindfulness meditation

In general, meditation can be categorized into two basic approaches based on how the attentional mental processes are associated: concentrative-based meditation and mindfulness-based meditation (Cahn and Polich, 2006). While concentration-based meditation focuses the attention on a single stimulus, mindfulness meditation associates with non-reactive observation of continually ongoing internal and external stimuli (Baer, 2003). Both types of meditation in fact involve mindfulness in the sense of non-judgmental acceptance, but the term “mindfulness meditation” is often used as a contrast to concentration meditation to indicate the difference in emphasis. Mindfulness meditation practice involves non-judgmental observation of sensations, thoughts, feelings, emotions, and environmental stimuli. It is a metacognitive process as it requires both mechanisms of attentional self-regulation and consciousness monitoring (Bishop et al., 2004; Semmens-Wheeler and Dienes, 2012).

A large body of research has explored the effect of mindfulness meditation training on cognitive abilities. Carter et al. (2005) found that individuals trained in meditation could measurably alter their experience of perceptual rivalry. Furthermore, long-term meditators show higher performance in the domains of sustained attention (Valentine and Sweet, 1999), executive attention (Chan and Woollacott, 2007; van den Hurk et al., 2010), and attention switching (Hodgins and Adair, 2010) as compared to matched controls. Studies investigating the effect of a 10-day and a 4-day short-term mindfulness meditation trainings respectively (Chambers et al., 2008; Zeidan et al., 2010) revealed improvement in working memory capacity in meditators following the mindfulness trainings. The latter study also observed that the meditators increased mindfulness levels over an active control group (Zeidan et al., 2010). Moreover, Tang et al. (2007) observed that the people who underwent a 5-day intensive mindfulness meditation retreat showed greater improvement in executive attention, better mood, and decreased stress-related cortisol compared with a control group. Higher attentional control and cognitive flexibility in experienced meditators are correlated with higher self-reported levels of mindfulness (Moore and Malinowski, 2009).

Recent research employing functional magnetic resonance imaging (fMRI) techniques suggests meditation-induced plasticity in the brain areas associated with cognitive control and emotional regulation. Lazar et al. (2005) demonstrated that long-term meditators had thicker cortices than non-meditators in the regions involved in sensory, cognitive, and emotional processing. Hölzel et al. (2011) found that an 8-week Mindfulness-Based Stress Reduction (MBSR) program led to an increase in gray matter concentration within the hippocampus, a domain involved in emotional regulation and response control (Fanselow and Dong, 2010).

The current study aims to examine the effect of mindfulness meditation training on the ability to control a BCI using motor imagery. Previous cross-sectional studies investigating EEG during hand motor imagery tasks demonstrated that experienced meditators had more distinguishable EEG patterns than untrained subjects (Lo et al., 2004; Eskandari and Erfanian, 2008). Thus, mindfulness meditation training may help to reduce “neural noise” and enhance signal-to-noise ratios and speed up the learning process in the use of BCIs (Davidson and Lutz, 2008).

Many previous studies on mindfulness meditation (Baer, 2003; Chiesa et al., 2011; Keng et al., 2011) utilized a randomized two-group design in which a mindfulness meditation intervention group is compared to a no-treatment or wait-listed control group. Such a design is limited in that it does not allow the researcher to control for nonspecific treatment effects such as expectancy and demand characteristics. The issues of expectancy and demand characteristic have been explored in consciousness research (Paskewitz and Orne, 1973; Plotkin, 1980) but they have not been clearly addressed in studies involving meditation interventions.

A recent paper (Zeidan et al., 2010) showed that mindfulness meditation increases performance on cognitive tasks. They used the "active control" of listening to the Hobbit being read to them. However, such a control may not elicit the same expectations of improvement in cognitive functioning as meditation. Jensen et al. (2012) found mindfulness based stress reduction compared with non-mindfulness based stress reduction improved selective attention, but it is also not clear whether expectations could account for these results although the control condition is closely matched to the treatment condition. To draw causal conclusions about the effectiveness of an intervention, researchers must compare the treatment condition with an active control and test whether both conditions shared the same expectations (Boot et al., 2013). The present study addressed this concern.

The present study used a three-group design, similar to Jensen et al. (2012), in which mindfulness meditation is compared not only against a no-treatment control condition but to another mental training condition. For the mental training condition participants received instructions in how to play a classical guitar. This novel control condition is designed on the theoretical basis that learning a musical instrument, like meditation, can be considered as a form of mental training that may be thought by subjects to be as likely to induce neuroplasticity and cognitive transfer among practitioners as meditation (Rabipour and Raz, 2012).

2.3 Musical training

Playing a musical instrument is a process that necessitate a highly sophisticated, multimodal coordination of sensory, motor, and cognitive processing. Activities that are continuously practiced by the musicians, e.g., pitch perception, attentive listening, musical sight-reading, synchronization between music and movement, composition, emotive transference, manual dexterity, remembering, learning, performing, and receiving multi-sensory feedback activate multiple core brain regions (Janata et al., 2002; Levitin and Tirovolas, 2009).

Previous studies comparing musicians with matched non-musicians have found brain structural and functional dissimilarities in musically related domains, including the auditory cortex (Pantev et al., 1998; Schneider et al., 2002; Bermudez and Zatorre, 2005), the sensorimotor cortex (Hund-Georgiadis and Von Cramon, 1999; Gaser and Schlaug, 2003) and multimodal integration areas (Gaser and Schlaug, 2003; Bangert and Schlaug, 2006; Sluming et al., 2007; Li et al., 2011). Studies also found that musicians performed better than non-musicians on auditory processing (Chartrand and Belin, 2006; Špajdel et al., 2007; Strait et al., 2010) and fine motor abilities (Amunts et al., 1997; Hughes and Franz, 2007; Spilka et al., 2010).

The effects on musical related domains (near transfer) are relatively common. Posner et al. (2008) proposed that art training may influence other cognitive processes and bring about far transfer effects through the underlying mechanism of attention. Moreover, studies conducted by Rueda et al. (2005) showed that attention training can lead to generalized improvement on other untrained domains. Along with the observations on music related domains, studies also revealed that musicians have greater abilities as compared to non-musicians on more distant domains, such as visual-spatial (Brochard et al., 2004; Sluming et al., 2007) and verbal working memory (Chan et al., 1998; Brandler and Rammsayer, 2003; Franklin et al., 2008). In addition, several experimental studies conducted on pre-school children and primary school children had demonstrated the effect of music training on spatial (Bilhartz et al., 1999), verbal (Ho et al., 2003), mathematical performances (Graziano et al., 1999), as well as general IQ (Schellenberg, 2004). Importantly, not only does music training have effects on cognitive functioning, people may believe that it does. Thus, we may be able to show that expectations are roughly the same for music and meditation trainings for enhancing BCI performance. Then meditation rather than music training leading to superior BCI performance would be particularly strong evidence for the claim that the effect of meditation training on BCI performance involves more than an expectancy effect.

CHAPTER 3

METHODOLOGY: THE PRESENT BCI SYSTEM

3.1 Introduction

The design and the operating principles of the present BCI system are presented in this chapter. The system uses spontaneous EEG signals produced during motor imagery of the right hand, the left hand or the feet movement as input. Output of the system can be used to control a motorized wheelchair, a prosthetic hand, and other devices. To investigate the effectiveness of the mindfulness meditation intervention, a BCI test was developed. The test examines the BCI control, also defined as "BCI performance" of an individual through a sequence of selection tasks.

3.2 The designs of the present BCI system

The components of the present BCI system are illustrated in Figure 3.1. The system consists of a data acquisition unit and a laptop computer as the processing unit. EEG signals associated with motor imagery are captured by electrodes as the input signals to the BCI. The analog input signals are amplified in a bipolar amplifier, digitized by a 16-bit analog-to-digital converter at the sampling rate of 256 Hz for each channel. Next, the digital data are sent to the computer batch-by-batch via a RS-232 interface or a Bluetooth communication module. The system supports 4 bipolar channels, that are 2 EEG channels, 1 electrooculogram (EOG) channel, and 1 electromyogram (EMG) channel.

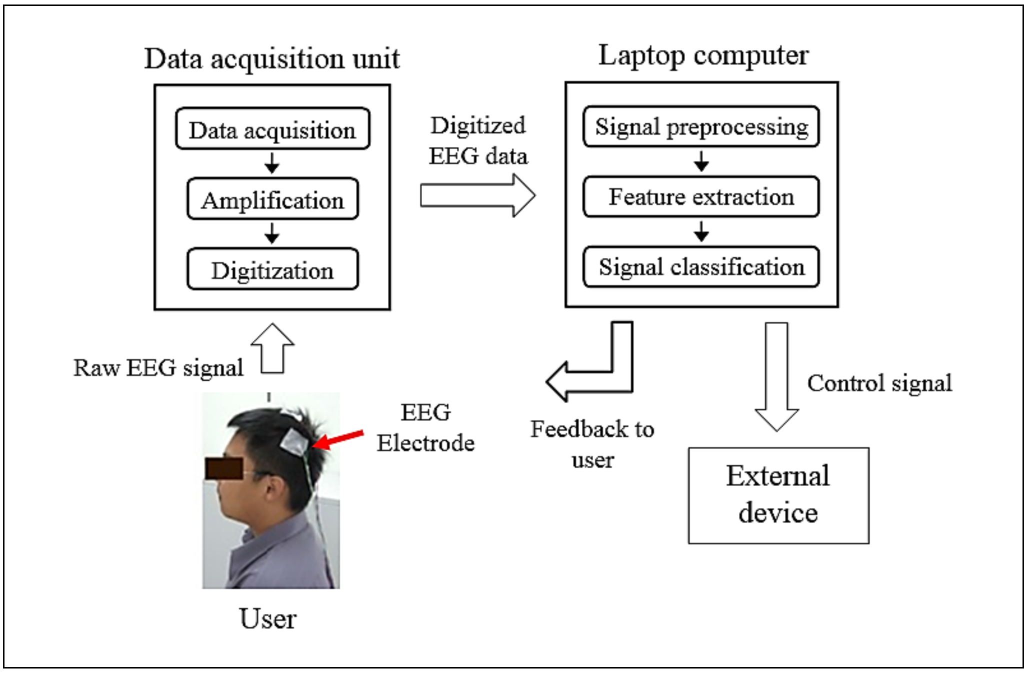


Figure 3.1 The components of the present BCI system.

The computer processes the digital data acquired by using a program written in visual C++ MFC language. First, the EEG data are checked for artifacts (for the training phase only, not applicable to the test and application phase) and filtered through a 5 - 40 Hz elliptic band pass filter to improve signal-to-noise ratio. Next, the coefficients of autoregressive (AR) modelling that represent the properties of the signals are estimated using Burg's method for every 1 second data with no overlap (Yong, 2005). The mathematical equation of AR process is shown by Equation 3.1.

$$y[n]=\sum_{k=1}^{p} a_k y[n-k]+w[n] \tag{3.1}$$

where *y[n]* is the current output; *w[n]* is the white noise with mean zero, σ^2 is the variance; a_k is the AR coefficients; and *p* is the AR model order.

The Burg's method minimizes the predicted errors and estimates the reflection coefficients directly with a recursive algorithm. For each recursion step, a single reflection coefficient is estimated. The reflection coefficients estimated are then applied in Levinson-Durbin algorithm to estimate the AR coefficients.

Linear discriminant analysis (LDA) is used as the classifier. The LDA output is used to provide feedback to the users and to generate control signals for output devices.

3.3 Offline EEG Experiment

The EEG signals during imagery of motor tasks are most strongly observed at the sensorimotor cortex region. However, the optimum locations of the EEG electrode that provide the most distinguishable EEG patterns from two different types of motor imagery task are subject-specific. Hence, a prior EEG scan with offline analysis was conducted to identify the optimum locations of the EEG electrodes and the best combination of the mental tasks for the each of the BCI users.

(a) Procedures

A commercial EEG system, the Nicolet 64-channel EEG acquisition system was used in the experiment. Nine electrodes were placed over the sensorimotor cortex area, as shown in Figure 3.2. All electrodes are referenced to an electrode placed on the forehead. These 9 common-referenced electrodes forms 9 bipolar

EEG channels as described in Appendix A. Non-EEG signals such as EOG and EMG were recorded along with the EEG signals to detect artifacts.

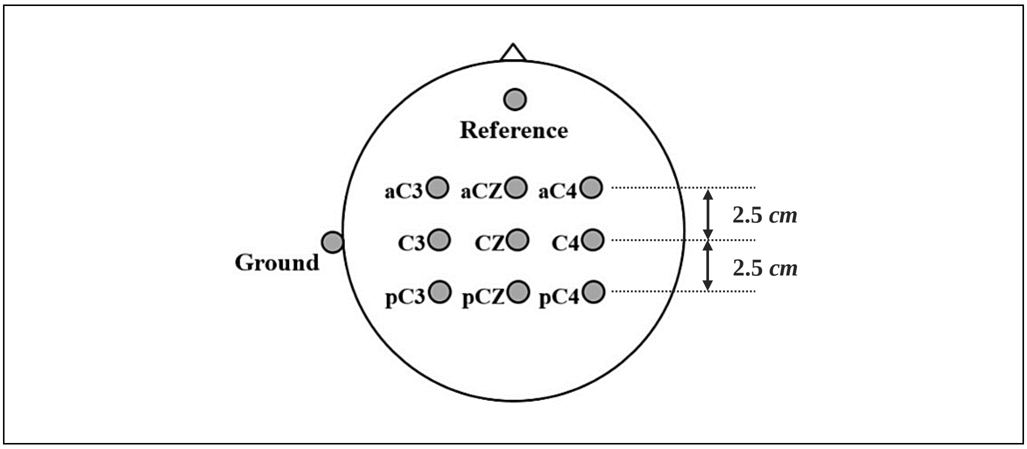


Figure 3.2 Montage used in the offline experiment.

The experiment recorded the EEG signals produced from 3 types of mental tasks: imagine left hand movement (LEFT), imagine right hand movement (RIGHT) and imagine both feet movement (FOOT). The subjects performed repetitive trials of 2 mental tasks (LEFT and RIGHT, LEFT and FOOT, or RIGHT and FOOT) in every session by following the commands displayed on the computer screen. Examples of the graphical user interface (GUI) for the experiment are shown in Figure 3.3. The order of the mental tasks in each session was randomized by the computer to avoid adaptation.

The experiment consisted of 6 sessions. Each session consisted of 40 trials (20 trials for each mental task) and lasted for about 10 minutes. Each trial lasted for 8 seconds. A trial started off with the command of READY LEFT, READY RIGHT, or READY FOOT for 3 seconds. This command allows the subject to get ready for the particular mental task and prepare to imagine. It also helps to prevent the subject from performing the wrong task. The command of

LEFT, RIGHT, or FOOT followed and continued for 5 seconds. During this duration, subjects imagined the motor movement repetitively. They were advised to engage in kinaesthetic imagery in addition to visual imagery. After 5 seconds, the command of REST was displayed. The resting interval between two consecutive imagery trials varied randomly between 5 to 10 seconds to avoid adaptation. The paradigm for a trial is shown in Figure 3.4.

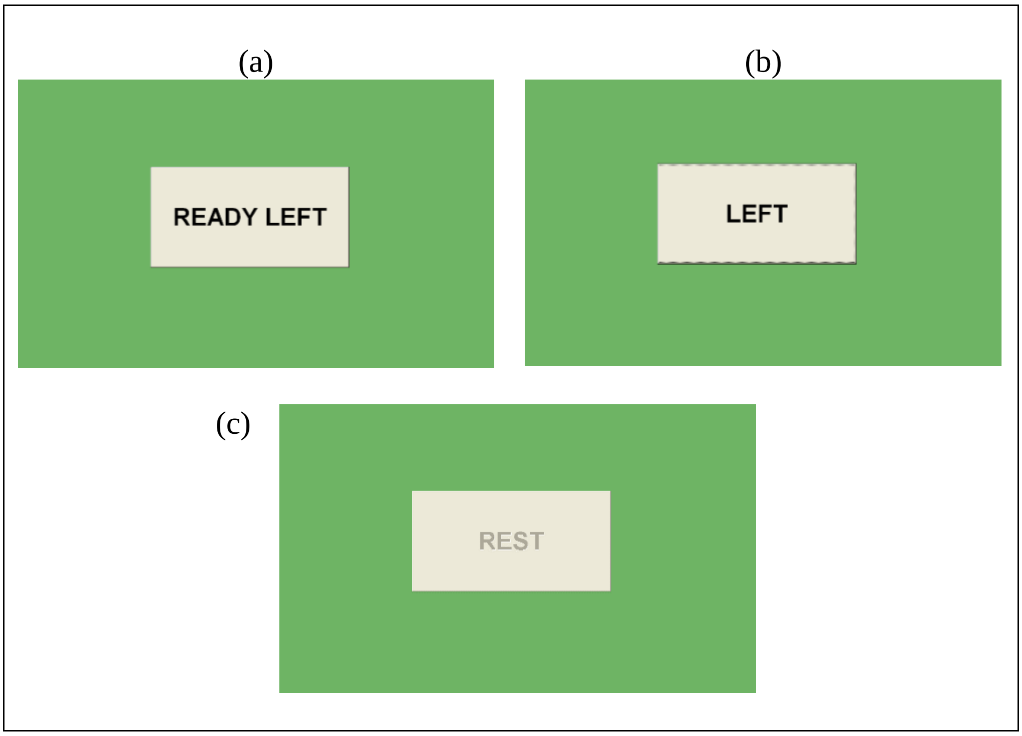


Figure 3.3 Examples of GUI in the offline EEG experiment: commands of READY LEFT, LEFT, and REST are displayed in (a), (b), and (c) respectively.

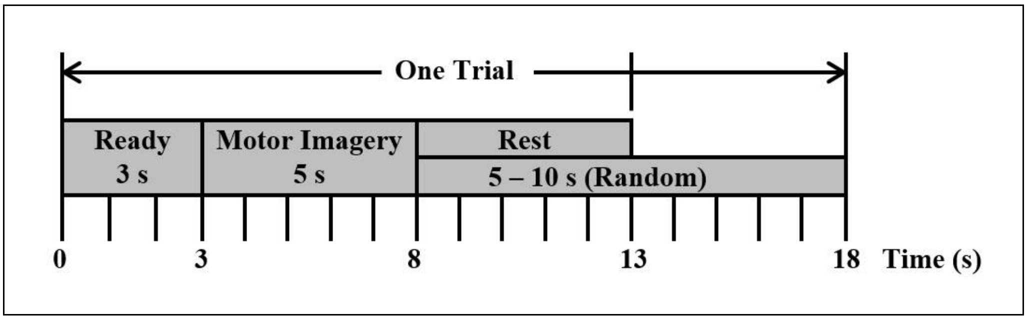


Figure 3.4 The paradigm of a trial.

(b) Offline analysis

The EEG signals recorded from the experiment were amplified in a bipolar amplifier and processed offline. The signal processing included artifact rejection, filtering, AR modelling, and LDA classification.

Analysis was carried out on each of the possible combinations of mental tasks and bipolar EEG channels. Three combinations of mental tasks were formed from the experiment, i.e., LEFT and RIGHT, LEFT and FOOT, and RIGHT and FOOT. Also, from the 9 bipolar EEG channels described in Appendix A, 36 possible bipolar EEG channel combinations (as shown in Appendix B) were derived for every mental task combination (Yong, 2005).

The average accuracy of the LDA 10 x 10 fold cross validation for each combination was calculated for each subject. The combination that gave the highest averaged accuracy was selected to be used in the subsequent online BCI experiment.

3.4 Online BCI experiment

The online BCI experiment involved repetitive trials of 2 types of mental tasks. It consists of a training phase and an application phase. The purpose of the training phase is to set-up the classifier. Artifact rejection algorithm was applied. Therefore only non-contaminated EEG trials were recorded for processing and to set-up the LDA classifier.

In the application phase, the classifier set up from the training phase was used to classify the ongoing EEG signals. Subjects could decide when to activate the desired control device by selecting the options from the selection menu displayed at the GUI. Feedback was provided to the subjects every second.

(a) Training phase

The experimental paradigm for the online training phase is similar to the one used in the offline EEG scanning except that fewer EEG channels were used and only 2 types of mental tasks were performed by the subjects. The combination of the EEG channels and mental tasks were selected based on the results of data analysis from the prior offline experiment (explained in Section 3.2 (b)). The training phase consisted of 3 sessions. Each session recorded data from 40 non-contaminated EEG trials (20 trials for each mental task) for processing. The duration of one session was about 10 minutes. It could be longer if the recorded data are contaminated with artifacts. The resting period between the 2 consecutive sessions was 5 minutes or longer if the user requested. The paradigm for a single trial is shown in Figure 3.4 (Section 3.2 (a)). Similar to the offline experiment, the duration for one EEG trial is 8 seconds in which 3 seconds are for ready and 5 seconds for actual motor imagery.

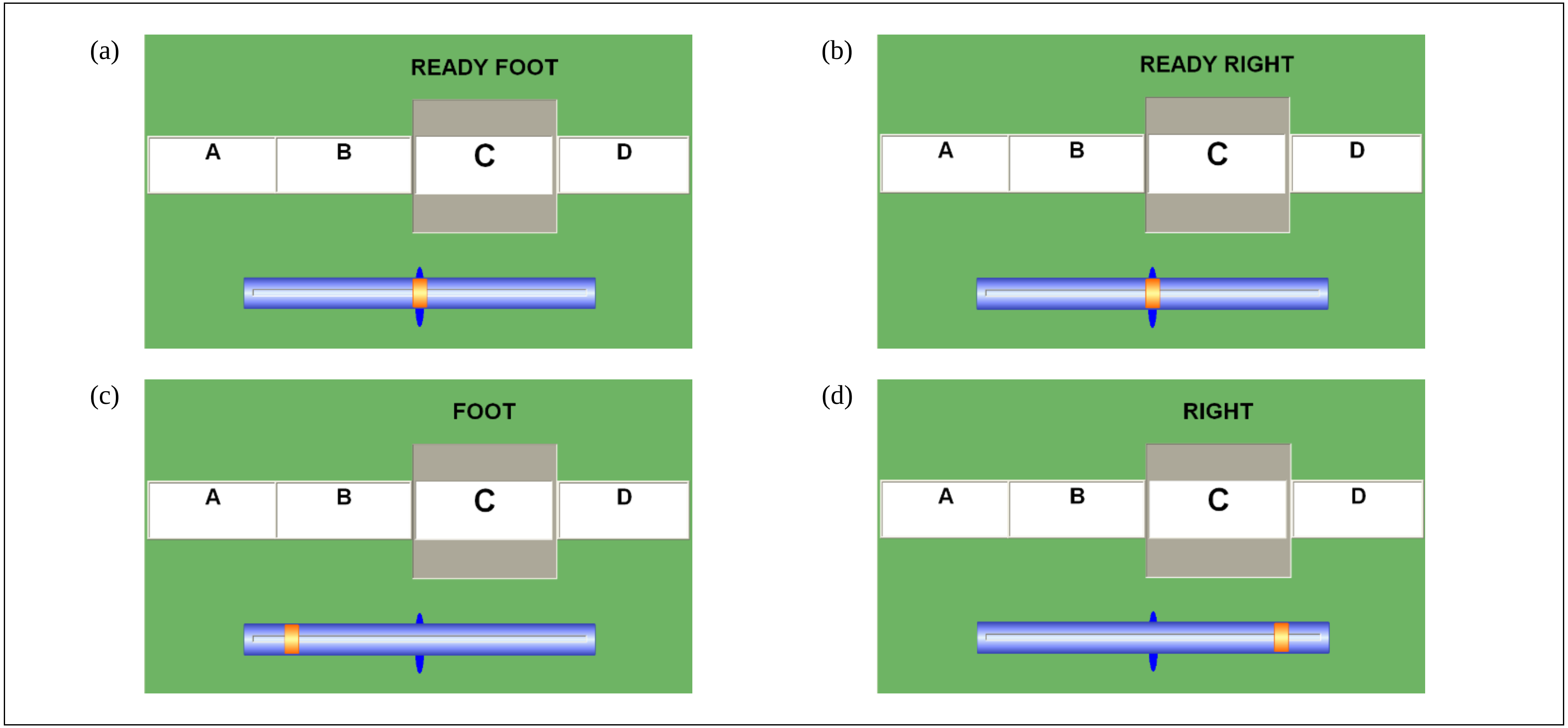


Figure 3.5 Examples of GUI in the BCI training phase: commands of READY FOOT, READY RIGHT, FOOT, and RIGHT are displayed in (a), (b), (c), and (d) respectively. For combination of mental tasks RIGHT and FOOT, cursor moving towards the left during FOOT (as shown in (c)) and towards right during RIGHT (as shown in (d)).

Figure 3.5 shows the examples of GUI used in the training phase. A horizontal cursor slider was presented to the user during the training phase. A cursor that was originally located at the center of the slider would automatically move towards the left or the right, a step every second for continuously 5 seconds according to the command given by the computer. The cursor would reach the end of the slider at the 5th second and it would move back to the center position when the command REST started. The direction of motion of the cursor that corresponds to different commands when different mental task combinations are used is described in Table 3.1.

Table 3.1 Direction of cursor movement corresponds to different commands for different mental task combinations.

Combination of mental tasks	Command	Direction of cursor movement
LEFT and RIGHT	LEFT RIGHT	Left Right
LEFT and FOOT	LEFT FOOT	Left Right
RIGHT and FOOT	RIGHT FOOT	Right Left

Artifact rejection algorithm using threshold method was applied during the training phase. Whenever artifacts were detected by the system from the non-EEG channels (EOG and EMG), the text of “BLINK” (indicating that the amplitude of the EOG was over the threshold) or “ARTIFACTS” (indicating that the amplitude of the EMG of chin was over the threshold) was displayed on the screen. At the completion of the experiment, all artifact-free EEG trials recorded were processed immediately by the computer and a classifier based on LDA weight vector was set up.

Next, the subject was required to rest for 2 minutes. The LDA classifier was used to classify the resting EEG 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 more than the other class, the LDA was considered bias to mental task 1. The mental task used in the application phase to make a selection during selection time (IM1) is dependent on the LDA bias class as shown in Table 3.2. In the case if no bias class is identified, either one of the mental tasks can be used as IM1.

Table 3.2 Mental tasks to be used in the application phase.

Bias Class	Mental task to be used during selection time (IM1)	Mental task to be used during non-selection time (IM2)
Mental task 1	Mental task 2	Mental task 1
Mental task 2	Mental task 1	Mental task 2
None	Either one of mental task 1 and mental task 2	The alternative mental task

(b) Application phase

In the application phase, the system processed and classified the on-going EEG signals real-time. No artifact rejection algorithm was applied. The GUI as shown in Figure 3.5 was used but with an additional selection menu. Subjects could decide when to activate the desired control device by selecting the options from the selection menu. Feedback was presented to the subject in the form of cursor movement on the slider at every second. The step size of the moving cursor varied from ¼ to 1 step per second dependent on the magnitude of the LDA classification output. The cursor would not move if the output was ambiguous.

At every 5 second, the cursor would move back to the center position of the slider. The detailed LDA classification rules and algorithm of the present BCI system were explained in Yong (2005). Feedback was also presented in the form of text on the top of the selection box to indicate the classification result.

3.5 Applications of the present BCI system

Feasibility of the present BCI system was demonstrated by interfacing the system with external devices. The system had been used to operate a prosthetic hand that could produce 4 types of hand movements (grasp, tripod, key pinch, and pulp-to-pulp pinch) and a 4-LED setting that represents 4 different remote devices (Goh et al., 2005; Yong, 2005).

Figure 3.6 The BCI-wheelchair in an indoor environment.

The system was also used to interface with an intelligent distributed-controlled wheelchair in an indoor environment, as presented in Figure 3.6 (Tan et al., 2008; Ng, 2011). For this application, the selection menu provided the users with 4 options of selection that represent 4 different locations in an indoor environment. Subjects used motor imagery to operate a binary switch in the BCI system (to select one of the predefined locations). The result of the selection was transmitted to the distributed controller of the motorized wheelchair. The wheelchair that was equipped with various kinds of sensors and a camera then self-navigated itself, past obstacles to reach the desired destination. Along the way to the destination, the subject did not have to exert any control over the movement of the wheelchair. They could free their mind and rest until the next selection. Seven healthy volunteers successfully completed the navigation test with varying completion times.

3.6 The BCI test

A BCI test was developed to measure how well the users could control the BCI continuously over a period of time. Figure 3.7 shows a GUI that was used in the BCI test. GUI-1 (Figure 3.7(a)) was designed for the selection of 4 options – “A”, “B”, “C”, “D”. The 4 selection options can be customized to represent any 4 types of selections, e.g., hand movements of a prosthetic hand (Goh et al., 2005) or different locations for a wheelchair (Tan et al., 2008).

The options “A”, “B”, “C” and “D” scroll from left to right. To select a particular option, the subject waits for the desired option to scroll into the grey selection box. By imagining the appropriate mental task, the subject moves the cursor to the right (or left depending on the mental task) of the cursor bar. The cursor has to be maintained to the right (or left) during 5 consecutive seconds and repeated a second time for another 5 seconds to confirm and to activate the selection of the desired option. If the subject failed to select the desired option in the grey selection box, he will have to wait for 15 seconds for the option to return to the selection box after it has scrolled through the next cycle. During the waiting period, no selection should be made.

In GUI-2 (Figure 3.7(b)), the text “RESET” is displayed at the selection box. GUI-2 was designed for the subject to ‘reset’ the menu each time after an option in GUI-1 is activated. Once “RESET” is activated, GUI-1 is displayed again to the subject for making the next selection.

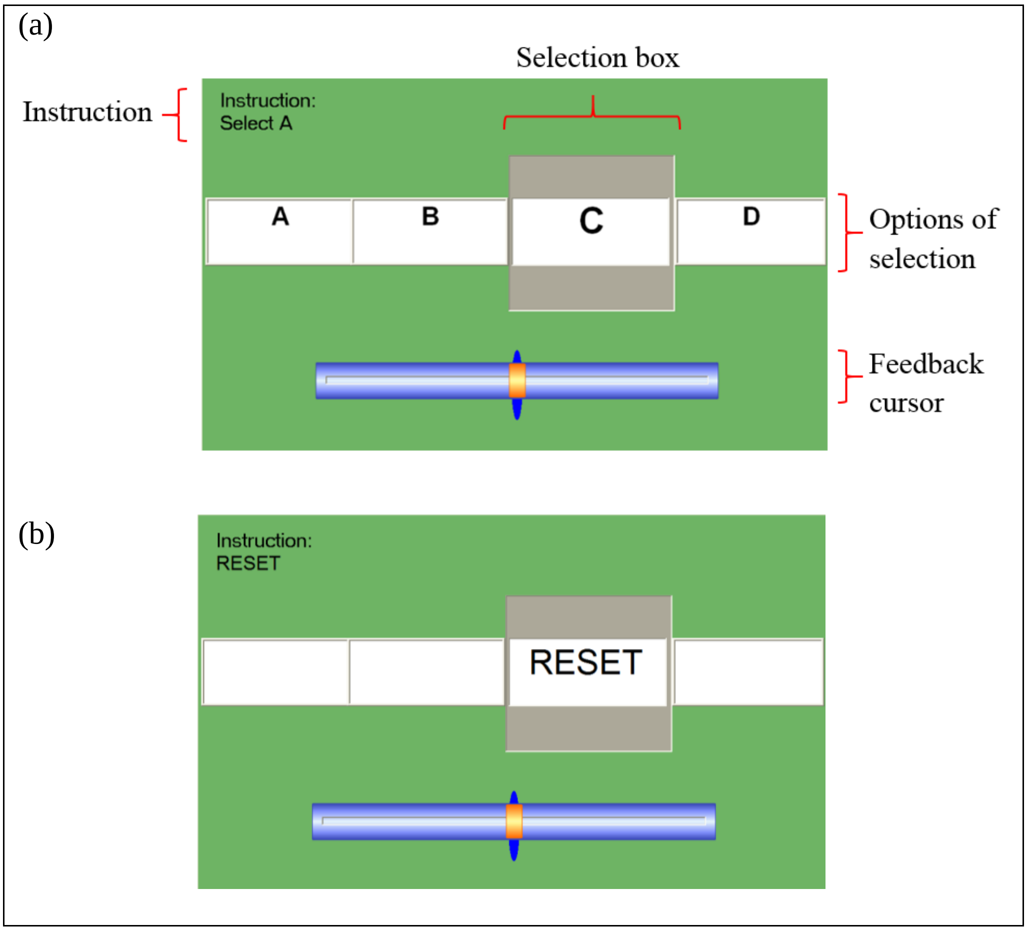


Figure 3.7 GUI used in the BCI test: (a) GUI-1 and (b) GUI-2.

For the purposes of the BCI test, a randomized sequence of selections was provided. Participants were required to make a selection according to the instruction given at the top left corner of the screen. An example of a randomized sequence of selections is as follows:

Select A → Reset → Select D → Reset → Select C → Reset → Select B → Rest for 30 seconds → Reset → Select C → Reset → Select A → Reset → Select B → Reset → Select D → Rest for 30 seconds → Reset → Select B → Reset → Select C → Reset → Select D → Reset → Select A → Rest for 30 seconds → Reset

The process flow of the test sequence is demonstrated in Figure 3.8. The operation principle for different conditions in the test sequence is illustrated in Figure 3.9. The optimum time to complete a test sequence of selections is 7 minutes.

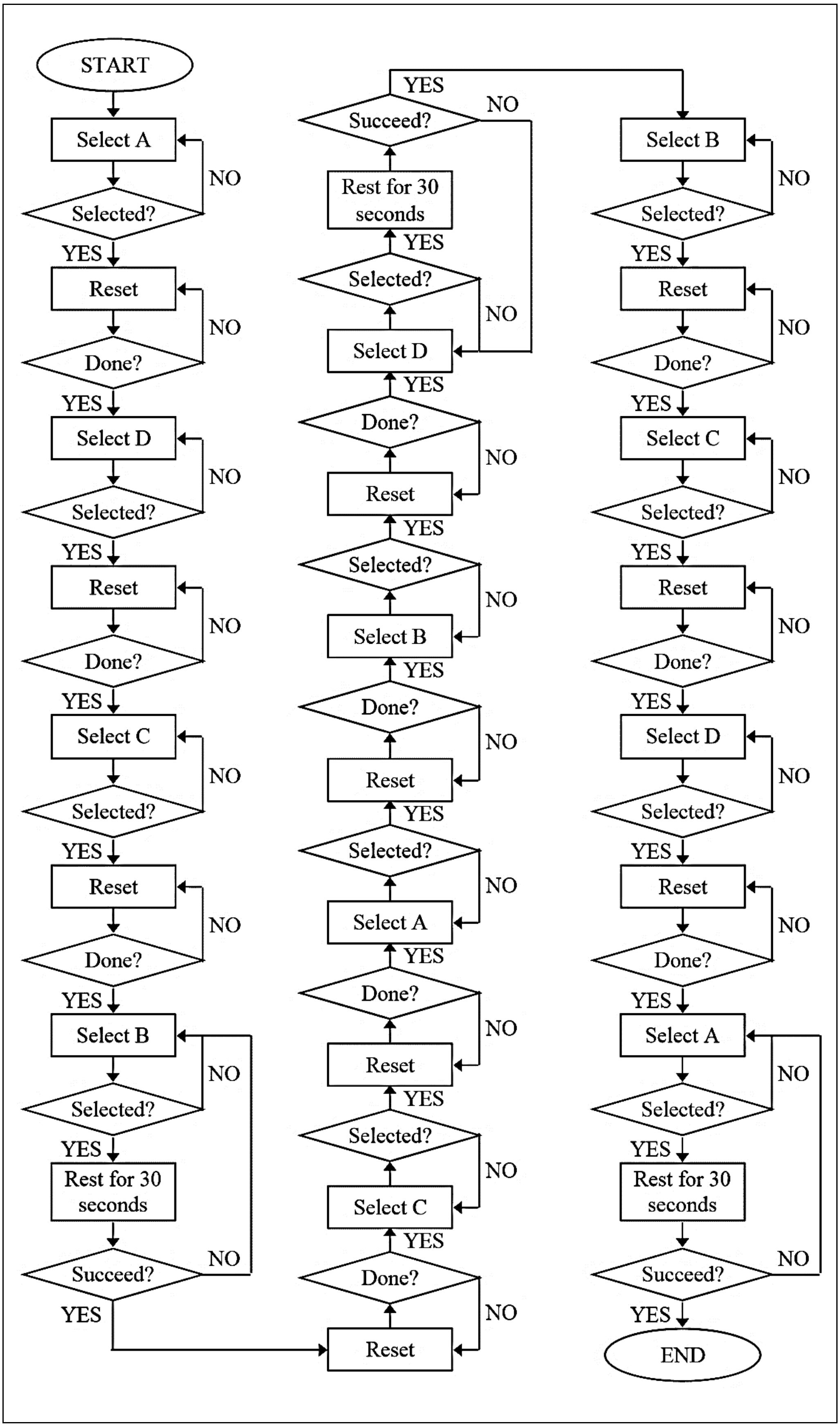


Figure 3.8 The process flow of an example of BCI test sequences.

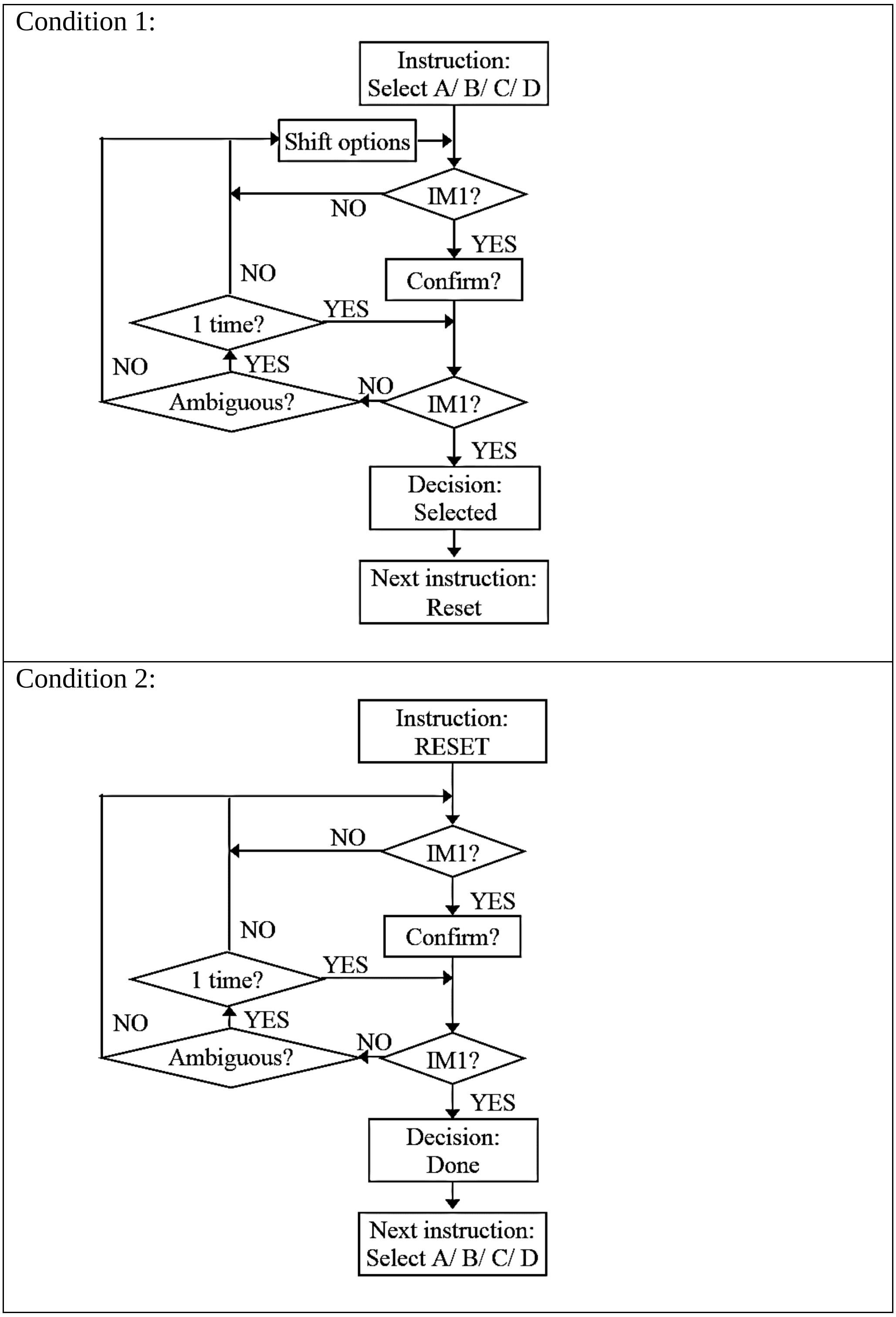


Figure 3.9 The operating principles of different conditions in the BCI test.

Condition 3:

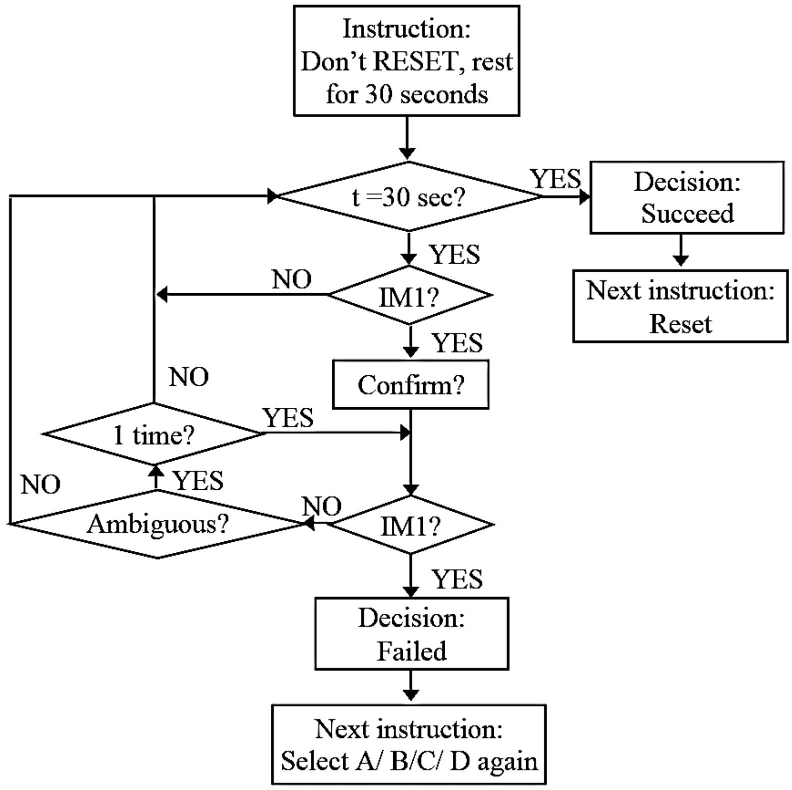


Figure 3.9 The operating principles of different conditions in the BCI test. (continued)

Table 3.3 shows the combinations of instruction given and the text displayed at the selection box in the GUI that describe the conditions for selection time and non-selection time. Participants should perform IM1 during the selection time and perform IM2 during the non-selection time.

Table 3.3 Conditions for selection time and non-selection time in the BCI test.

GUI	Instruction	Text displayed in the selection box	Selection Time	Non-selection time
GUI-1	Select A	A	√	
		B / C / D		√
	Select B	B	√	
		A / C / D		√
	Select C	C	√	
		A / B / D		√
	Select D	D	√	
		A / B / C		√
GUI-2	RESET	RESET	√	
	Rest for 30 seconds	RESET		√

Table 3.4 Confusion matrix formed from different classification conditions in the BCI test.

	Selection time	Non-selection time
Correct response	True positive (TP)	True negative (TN)
Incorrect response	False negative (FN)	False positive (FP)

The four types of classification from the BCI test are True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) making a confusion matrix as shown in Table 3.4. The BCI performance is measured by the accuracy (Wolpaw and Wolpaw, 2012) which is defined as follow:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.2}$$

CHAPTER 4

METHODOLOGY: THE RANDOMIZED CONTROLLED TRIAL STUDY

4.1 Introduction

A survey study was conducted prior to the main study. The purpose of the survey is to compare the people's expectations on mindfulness meditation and music interventions. More specifically, it was to know whether both interventions shared the same expectations. Then, the main study was conducted to investigate and compare the effect of the mindfulness meditation and music trainings on the BCI users. Data collected from both studies were analyzed using statistical methods.

4.2 Survey study

(a) Participants

A questionnaire norming study was conducted on 40 undergraduates who were randomly recruited from a Malaysian university to measure how expectations for mindfulness meditation and music training would affect BCI performance. All participants were engineering students between 18 and 22 years old. They were Chinese males and had never taken part in any formal meditation or music training. They were informed that no incentives of any kind would be given for their participation in the study.

(b) Design and procedure

Participants were asked to read the paragraphs that describe the scenarios of a) a 12-week mindfulness meditation training and b) a 12-week training on learning to play classical guitar. The order of both scenarios was counterbalanced across participants. In each scenario, the BCI test was explained to the participants. Participants then indicated whether they expect the training would improve, degrade, or cause no change to BCI performance. Participants also rated on a 1 to 10 scale to indicate the strength of their expectation (e.g., How strongly did they believe that the meditation training would make them improve on the BCI test? They were to give an answer on a 1 to 10 scale, where 1 indicated just guessing and 10 indicated certainty). A sample of the questionnaire is shown in Table 4.1.

Table 4.1 A sample of questionnaire in the survey study.

Instructions: Please imagine the following scenarios and indicate your answer to the following questions by rating on a 1 to 10 scale. **<u>Scenario 1</u>** Imagine a group of people attend a meditation training program for 12 weeks, attending a one hour session each week. They are taught some formal meditation skills, such as sitting, walking and lying down meditation by a highly qualified meditation instructor.

Table 4.1 A sample of questionnaire in the survey study. (continued)

Questions:

These days scientists can pick up brain waves and use them to control devices. By asking a person to imagine one thing to move a device to the left and another thing to move the device to the right, people can by "thought power" move the device because the scientist can distinguish the different brain waves. But a person must concentrate hard to be able to do this; if they are distracted they cause either no movement or the wrong movement.

(a) What do you expect the meditation training would make them on this task? [improve / degrade / cause no change]

(b) How strongly do you believe that the meditation training would make them (improve / degrade / cause no change) on this task?

Give your answer on a 1 to 10 scale, where 1 means you are just guessing and 10 means you are certain that there will be some improvements.

1 2 3 4 5 6 7 8 9 10

← Guessing ... Certain →

4.3 BCI Study

The study started with a recruitment drive around the campus. Then baseline assessment, randomization of participants, post-intervention assessment, and statistical analyses on the measures followed. Details of each process are explained in the following sections.

(a) Participants

Participants for the main BCI study were independent from the participants for the survey study although both studies were conducted in the same campus. Participants were recruited through in campus advertisements and announcements. A total of 76 participants were recruited into the study.

Prior to the enrolment of the study, the eligibility of the interested participants was screened through the use of a demographic form (showed in Appendix C) and a phone interview. The eligible participants were those who had no previous experience in a formal practice related to mindfulness meditation and had no more music training than the obligatory musical education at primary school. They also did not have any existing or prior history of neurological or psychological disorders and brain injury or brain-related trauma.

All the participants recruited were given detailed explanations on the study procedures and were required to complete a written informed consent form (Appendix D) before the beginning of the baseline assessment. Participants were randomly assigned to study groups according to a computer-generated random number list. Randomization was conducted after they completed the baseline assessment in order to avoid any of the participants dropping out from the study before the assessment causing unequal sample size between groups. The experimenter was aware of the group allocation of the participants.

(b) Design and procedure

The programs of the study were scheduled according to the university semester timetable. The baseline assessment was conducted before the beginning of the semester. Participants attended an EEG scanning (explained in Section 3.2) followed by a BCI test on another day. Each session was about 2 hours. Participants were allowed to choose the timeslots from a list given based on their available time. Participants were told to make certain preparations for each test session, for instance having enough sleep (not less than 5 hours), not consuming caffeine or alcoholic beverages, and not performing active exercise for 12 hours prior to the test session. Participants were paid 25 Malaysian Ringgit (equivalent to approximately 8 US Dollars) for completion of each test session.

Following baseline assessment, participants were randomly assigned into 3 study groups: a meditation group, a music group, and a control group. Intervention programs were started at the beginning of the new semester and ended 12 weeks later. The intervention groups must fulfill 80% attendance to the programs. The instructors for mindfulness meditation and music trainings were blind to the content of the assessment.

Participants in the meditation group attended a mindfulness meditation intervention training that was delivered by a mindfulness meditation instructor who had twenty years of experience of teaching meditation. The training sessions were held once a week for 12 weeks. The duration for each training session is 1 hour. Each session was conducted with groups of 6 to 10 participants. The participants were taught the concepts and skills of how to practice mindfulness meditation without any spiritual element and religious emphasis. They were also taught on how to be always mindful in their daily activities. Each training session included a 20-minute sitting meditation. Participants were guided by the instructor to sit quietly and focus on the flow of their natural breath, with their eyes closed. The participants started by learning to feel the physical sensation of the air flowing in and out from the body. Then they were guided to become aware of and have non-reactive observation on their thoughts, senses, and feelings as they arise. They were told to not look for any thought or remain alert waiting for any thought to come but to notice the content of each thought when it arises, accept it, and allow it to go. They were also told to gently focus back on the breath when they noticed that their mind had wandered. As the intervention progressed, the participants were guided with more instructions and details about mindfulness practice. For instance, they were taught to calm down the mind by remaining focused on their breath and to perform a "body scan" – bringing awareness to the physical sensations throughout the whole body (experience each individual parts of the body in more detail, e.g., elbow, lower arm, wrist, palm, fingers, etc.) while nonjudgementally allowing the random discursive thoughts to simply arrive and go. Sometimes, the participants had additional walking or lying down meditation exercises. Before and after each practice session, participants were given time for discussions. They were encouraged to share their experience and to ask questions about difficulties and doubts during meditating. In addition, participants were assigned to perform 20 minutes home practice per day of mindfulness meditation. They were also encouraged to be aware of the body and mind processes throughout their daily activities.

Participants in the music group learned to play a classical guitar under the guidance of a professional instructor from a local music center. The training sessions were held once a week for 12 weeks. Each training session was conducted in groups consisted of 5 to 7 participants and continued for 1 hour. The participants learned various basic techniques of playing a classical guitar, such as understanding the notes, positioning the fingers, pressing strings, tuning, plucking, strumming, and playing the chords and melody. The lesson was conducted based on the syllabus designed by Yamaha Music Foundation (Foundation, 2007). Participants were assigned to perform 20 minutes home practice each day.

Participants in the control group were told to not participate in any activities that relate to the meditation training or learning a musical instrument during the intervention period.

Each participant was required to submit a log book. Participants from the meditation group and the music group were required to record and described their daily practices. The participants from the control group have to record and confirm every week that they were not involved in activities that were related to the intervention program.

4.4 Statistical analyses

Data obtained from both the survey study and the BCI study were analyzed statistically using conventional hypothesis testing approach and the Bayesian approach.

(a) Conventional hypothesis testing approach

The conventional hypothesis testing analyses were carried out using Statistical Package for the Social Sciences (SPSS) program. A significance level of $p = .05$ was used. For any non-significant finding, confidence interval was calculated to access the sensitivity of the null result.

For the survey study, descriptive statistics for the measures of expectation on the two training programmes were generated. The expectations on two training programmes were compared by their odds ratio and using a chi-squared test of independence for categorical variables and an independence-samples t test for continuous variables.

For the BCI study, descriptive statistics for the BCI performance of completers from the three treatment conditions were generated. The between-group differences before intervention were assessed with a one-way analysis of variance (ANOVA) using the intervention condition as independent variable and the baseline BCI score as outcome variable. Then the main effect of between-group differences after intervention was evaluated with a one-way analysis of covariance (ANCOVA) using the intervention condition as independent variable, the post-test BCI score as outcome variable, and the baseline BCI score as covariate. The post hoc tests with sequential Bonferroni correction procedure (Hochberg, 1988) is followed if a significant main effect is found.

(b) Bayesian approach

In the Bayesian analyses, the Bayes factor was calculated using a Bayes factor calculator programme developed with Microsoft Visual C# language. A brief description of the Bayes factor is given below.

In an experiment that consists of 2 particular hypotheses, with H_1 the experimental hypothesis and H_0 the null, the Bayes factor, B_{10} is defined as

$$B_{10} = \frac{p(D|H_1)}{p(D|H_0)} \tag{4.1}$$

where $p(D|H_1)$ is the probability of obtaining the data, given the experimental hypothesis H_1 and $p(D|H_0)$ is the probability of obtaining the data, given the null hypothesis H_0. A derivation of the Bayes factor is shown in Appendix E.

The marginal likelihood, $p(D|H_k)(k = 0, 1)$ can be obtained by integrating over the parameter space and computed using numerical methods.

$$p(D|H_k) = \int p(D|\theta_k, H_k)\pi(\theta_k, H_k)d\theta_k \text{ , k = 0, 1} \tag{4.2}$$

where θ_k is the parameter under hypothesis H_k; $\pi(\theta_k|H_k)$ is the prior density of H_k ; $p(D|\theta_k, H_k)$ is the probability density of D given the value of θ_k, which is also called the likelihood function of θ_k.

Therefore

$$B_{10} = \frac{\int_{\theta_1 \in \Theta_1} p(D|\theta_1, H_1)\, \pi(\theta_1|H_1) d\theta_1}{\int_{\theta_0 \in \Theta_0} p(D|\theta_0, H_0)\, \pi(\theta_0|H_0) d\theta_0} \tag{4.3}$$

A simple Bayes factor calculator programme was developed based on the assumptions (Dienes, 2008) as described in Table 4.2. The program codes of the calculator are displayed in Appendix F. The calculator gives a *B* value after the user enters the sample mean difference and the associated standard error (SE) and defines the characteristics of the prior distribution of the experimental hypothesis. The output computed from the calculator programme was confirmed with the values obtained from Dienes's online Bayes factor calculator (Dienes, 2008).

Bayes factors suggest three different conclusions: strong evidence for the alternative; strong evidence for the null; and insensitive result. More specifically, Jeffreys (1961) proposed that Bayes factor larger than 3 or less than 1/3 indicates strong evidence; conversely, anything between 1/3 and 3 represents weak or "anecdotal" evidence (also discussed in (Dienes, 2014). A rule of thumb for interpreting the confidence level of Bayes factor is depicted in Figure 4.1.

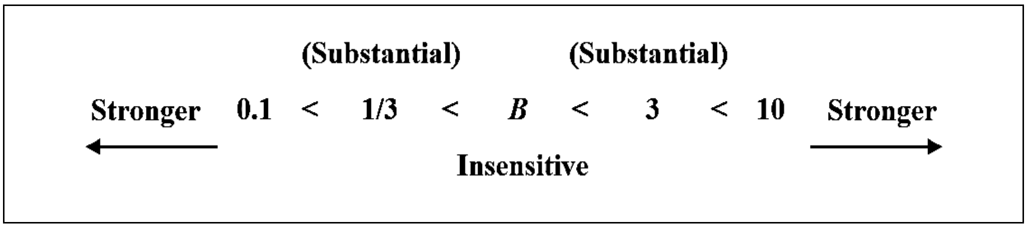


Figure 4.1 A rule of thumb for interpreting the confidence level of Bayes factor.

Table 4.2 Assumptions used in developing the Bayes factor calculator.

1. It is assumed that the data D is normally distributed around the population mean x with a known variance σ^2,

$D \sim$ N $(x\ ,\ \sigma)$

$$p(D|\theta_k, H_k) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\theta_k)^2}{2\sigma^2}}$$

2. For null hypothesis H_0 :

$\theta_0 = 0$, $\pi(\theta_0|H_0) = 1$

$$p(D|H_0) = p(D|\theta_0 = 0) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

3. For experimental hypothesis H_1 :

(i) If we approximate the plot of plausibility against different possible population mean differences θ_1 by a uniform distribution from a lower limit θ_L and upper limit θ_U,

$\theta_1 \sim$ uniform $(\theta_L\ , \theta_U)$

$\pi(\theta_1|H_1) = \frac{1}{\theta_U - \theta_L}\ , \theta_L \leq \theta_1 \leq \theta_U$

$p(D|H_1) \approx \sum_{i=0}^{m} \left[\frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-[\theta_L+i\Delta])^2}{2\sigma^2}} \times \frac{1}{\theta_U-\theta_L} \times \Delta\right]$, where $\Delta = \frac{\theta_U-\theta_L}{m}$ and m is the number of step.

Table 4.2 Assumptions used in developing the Bayes factor calculator. (continued)

(ii) If we approximate the plot of plausibility against different possible population mean differences θ_1 by a normal distribution with mean μ and standard deviation σ_1,

$\theta_1 \sim N(\mu\,,\sigma_1)$

$\pi(\theta_1|H_1) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(\theta_1-\mu)^2}{2\sigma_1{}^2}}, -\infty < \theta_1 < \infty$

$p(D|H_1) \approx \sum_{i=0}^{m} \left[\frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-[\theta_L+i\Delta])^2}{2\sigma^2}} \times \frac{1}{\sqrt{2\pi}\sigma_1} e^{\frac{-([\theta_L+i\Delta]-\mu)^2}{2\sigma_1{}^2}} \times \Delta\right],$

$\Delta = \frac{10\sigma_1}{m}, \theta_L = \mu - 5\sigma_1$

(iii) If we approximate the plot of plausibility against different possible population mean differences θ_1 by a half normal distribution with mean μ and standard deviation σ_1 (we assume the predicted difference is in the positive direction),

$\theta_1 \sim \frac{1}{2} N(\mu\,,\sigma_1)$

$\pi(\theta_1|H_1) = \frac{2}{\sqrt{2\pi}\sigma_1} e^{-\frac{(\theta_1-\mu)^2}{2\sigma_1{}^2}}, 0 \leq \theta_1 < \infty$

$p(D|H_1) \approx 2\sum_{i=0}^{m} \left[\frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-[\theta_L+i\Delta])^2}{2\sigma^2}} \times \frac{1}{\sqrt{2\pi}\sigma_1} e^{\frac{-([\theta_L+i\Delta]-\mu)^2}{2\sigma_1{}^2}} \times \Delta\right],$

$\Delta = \frac{10\sigma_1}{m}, \theta_L = \mu$

CHAPTER 5

RESULTS

5.1 Analyses on EEG spectrum

An example of the EEG spectrum of one of the participants is presented in Figure 5.1. Graphs (a) and (b) are for baseline and (c) and (d) are for post-test. The power spectral density of the EEG was estimated via autoregressive (AR) analysis using Burg's method. The EEG signals of the participant were acquired from channel ac_C3 and channel ac_CZ during the trials of motor imagery of feet movement (FOOT) and right hand movement (RIGHT) in the BCI test. Note that C3 and CZ are the active representation areas for motor imagery of right hand and foot respectively. The mental tasks used are FOOT and RIGHT. As shown in the graph, the participant achieved highest power spectral density within frequency domain of mu rhythm (peak at 12 Hz) at channel ac_CZ during imaginary FOOT for both baseline and post-test.

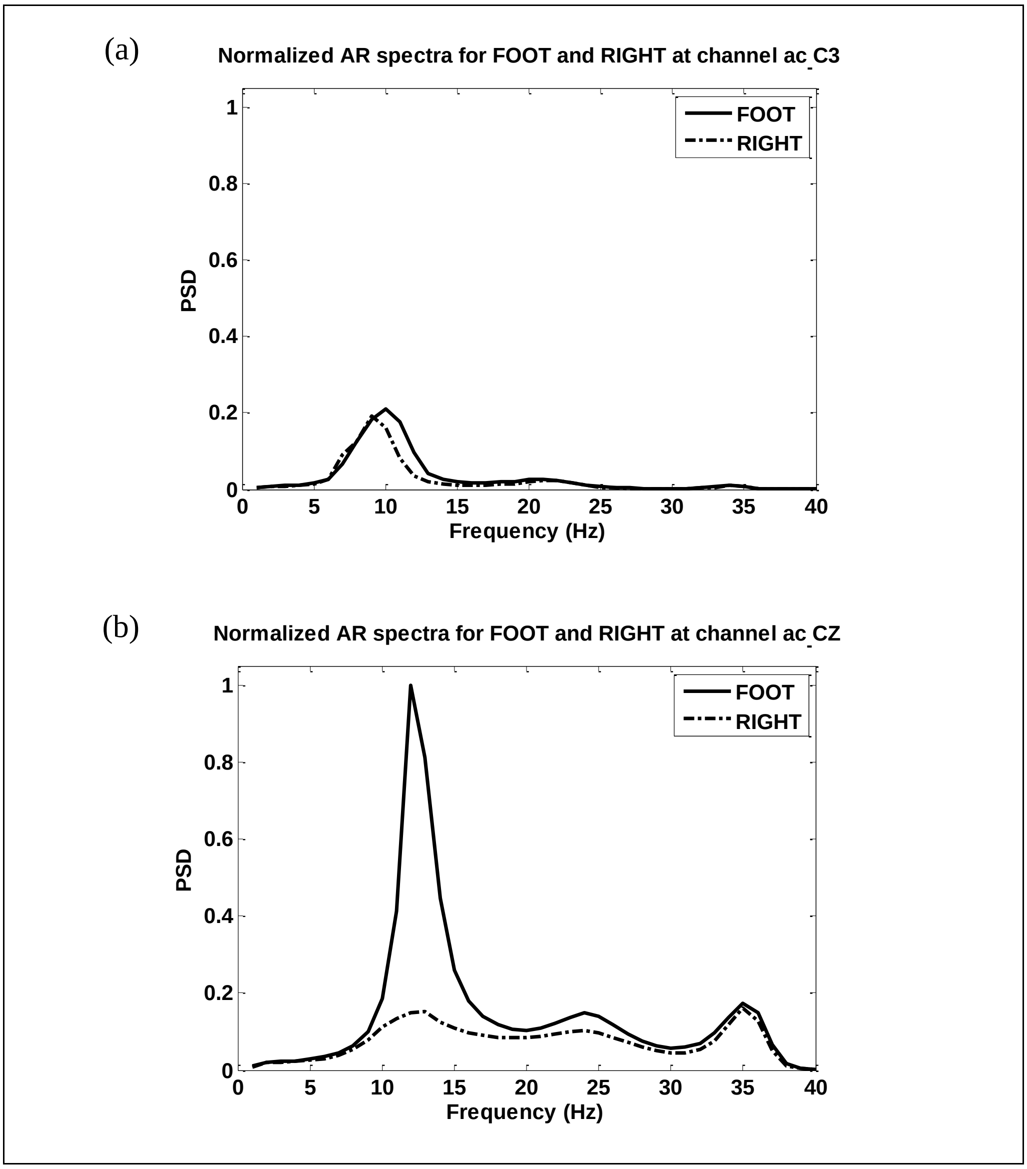
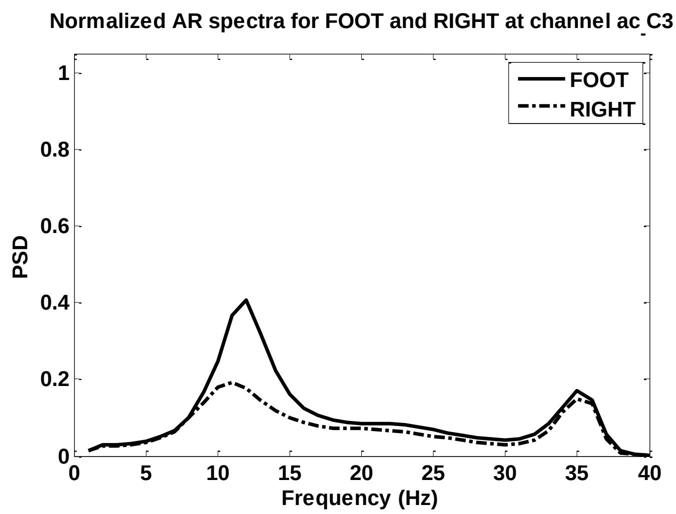
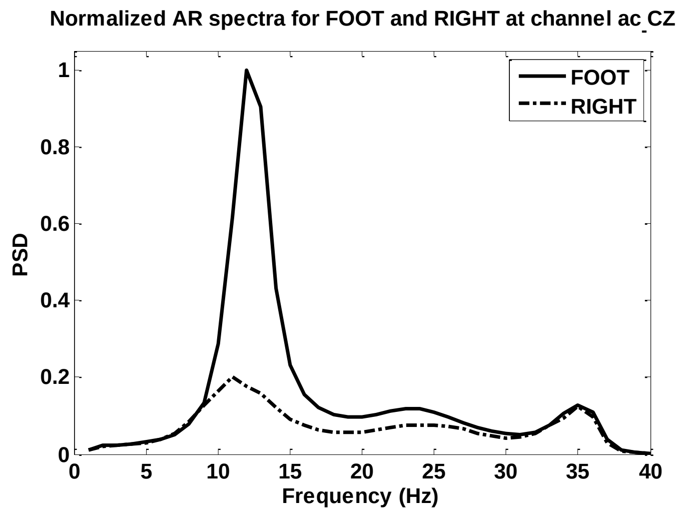


Figure 5.1 Mean AR spectra of a participant in the BCI test at: (a) channel ac_C3 during baseline, (b) channel ac_CZ during baseline, (c) channel ac_C3 during post-test, and (d) channel ac_CZ during post-test. The power spectral density was normalized to the highest peak of the mean spectrum in the session.

(c)



(d)



Note:
Mental task used: FOOT and RIGHT
Mental strategy used: FOOT - Imagine the feeling of moving the leg upwards and downwards repetitively (kinaesthetic imagery), RIGHT - Imagine the feeling to move the right hand when the hand was not allowed to move (kinaesthetic imagery)

Figure 5.1 Mean AR spectra of a participant in the BCI test at: (a) channel ac_C3 during baseline, (b) channel ac_CZ during baseline, (c) channel ac_C3 during post-test, and (d) channel ac_CZ during post-test. The power spectral density was normalized to the highest peak of the mean spectrum in the session. (continued)

Figure 5.2 shows the R^2 spectral analysis at channel ac_C3 and ac_CZ for the same participant in both baseline and post-test. The R^2 spectral analysis provides us the general view on the EEG discriminating features in the frequency domain at different EEG channels for discrimination of two mental tasks. A higher value of the R^2 indicates a better discrimination of the two mental tasks and a better EEG control in the BCI test. The R^2 spectra of the participant indicated that channel ac_CZ provides better discrimination for FOOT and RIGHT when compared with channel ac_C3, in both sessions. The participant scored an accuracy of 54% in the baseline BCI test and 82% after 12-week meditation training. This may be explained by the R^2 distribution between the frequency range of 18 Hz to 23 Hz for post-test that is significantly higher than those at the baseline and, as a result, provides a better classification accuracy at the post-test.

The above description is a demonstration of an analysis of the EEG data of a particular participant. The recorded EEG signals are very subject sensitive and can depend on many other factors. A full analysis of the EEG data of all the participants will be a subject for a future study. The strategy in the present study is to use a randomized controlled trial on a large enough sample to arrive at a conclusion.

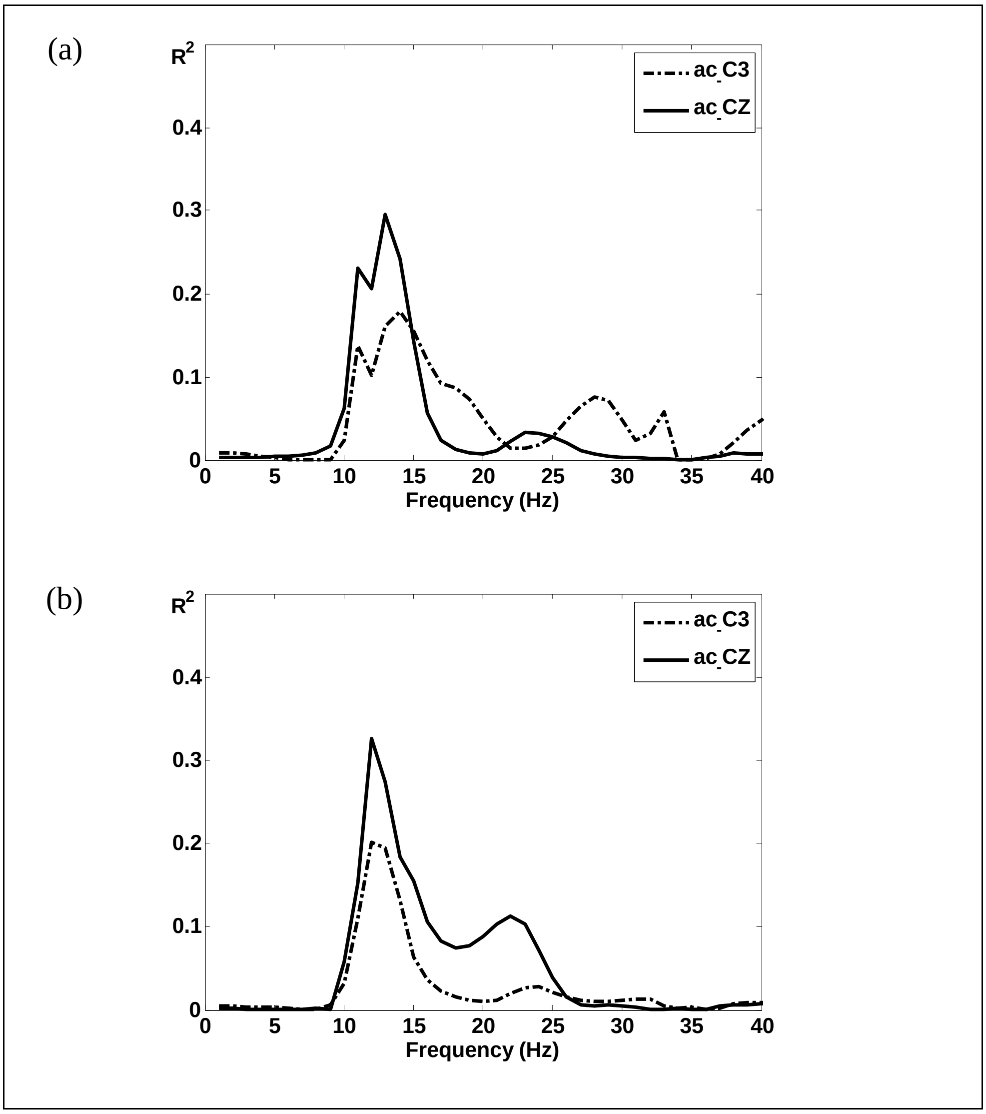


Figure 5.2 The R^2 spectra of channel ac_C3 and channel ac_CZ for discrimination of imaginary feet movement (FOOT) and imaginary right hand movement (RIGHT) at (a) baseline and (b) post-test.

5.2 Results of the survey study

Forty participants completed the questionnaire survey. Table 5.1 summaries the data of the survey study. Results showed that the majority of participants expected that both meditation training and music training would improve the BCI performance; a minority thought they would have no effect. Specifically 80% of the participants thought meditation would improve BCI performance rather than not and 78% of the participants thought music training would improve BCI performance rather than not. The odds ratio for the probabilities of expectation was calculated as follows:

$$Odds\ ratio = \frac{p(med)/(1 - p(med))}{p(mus)/(1 - p(mus))} \tag{5.1}$$

where *p(med)* is the probability that people think meditation will improve BCI performance, and *p(mus)* is the same for music training.

If *p(med)* and *p(mus)* were the same, then the odds ratio would be 1 (i.e., no association between expectation and training). For the data, *p(med)* = .80 and *p(mus)* = .775, so odds ratio for these probabilities was (.80/.20 * .225/ .775) = 1.16. Results from chi-squared test of independence showed that there was no significant association between expectation and training, $\chi^2(1) = .07$, $p = .78$. The 90% confidence interval for the odds ratio was [.47, 2.86]. The interval includes 1, indicating no significant association between expectation of change and type of training even at the 10% significance level.

Table 5.1 Mean (standard deviation) of the expectations from the norming study on 40 participants' expectations that meditation training and music training would affect the BCI performance.

	Sample 1		Sample 2				
	n1	Mean (SD)	*n2*	Mean (SD)	*n*	*t*	*P*
Expectation for meditation training:							
Improve	17	6.76 (1.72)	15	6.60 (2.06)	32	.25	.81
No Change	3	7.00 (1.73)	4	5.75 (3.86)	} 8	.51	.63
Degrade	0	-	1	-		-	-
Expectation for music training:							
Improve	15	6.93 (2.02)	16	7.00 (1.63)	31	- .10	.92
No Change	5	5.00 (2.55)	4	5.00 (1.63)	} 9	.00	1.00
Degrade	0	-	0	-		-	-

Note: Participants in Sample 1 were presented with paragraphs that described the meditation training as the first scenario and the music training as the second scenario. The order for the scenarios was counterbalanced on Sample 2. Odds ratio = (32*9) / (31*8) = 1.16; test of independence $\chi^2(1) = .07$, $p = .78$.

Further, the upper limit of the interval indicates that odds ratio in favor of meditation over music could be at most 2.9; e.g., if the probability for expecting a positive change with music training was 72% it would be 88% for meditation training. Given this is the upper end of the confidence interval, similar expectations of positive change to a high degree of sensitivity have been established. Putting a confidence interval on an odds ratio allows one to assess the sensitivity of the null result; contrast simply obtaining a non-significant chi-squared test of association. Note the confidence interval assumes independence of observations, whereas each respondent gave an answer for both training conditions.

Table 5.2 Summary of counts showing relation between expecting change from meditation training and expecting change from music training.

Expectation for meditation training:	Expectation for music training: Improve	Not improve
Improve	26	6
Not improve	5	3

From the data summarized in Table 5.2, no correlation between the answers for music and for meditation was detected, odds ratio = (26*3)/(5*6) = 2.60; test of independence $\chi^2(1) = 1.29$, $p = .26$. The 90% CI for odds ratio is [0.64, 10.64], indicating the assumption of independence was true within broad limits.

A more sensitive demonstration of the equivalence of expectations was obtained by looking at the continuous strength of expectation, as shown in Figure 5.3. There was no significant difference in the strength of expectation for meditation (M = 6.69, SD = 1.86) and music (M = 6.97, SD = 1.80) trainings;

$t(61) = -.61$, $p = .55$, 95% CI on the difference [-1.2, .6]. That is, the strength of expectation could only be greater for meditation than music by .6 of a scale point, where the scale is from 1 (guessing) to 10 (certainty). It means that the data allow only a tiny difference in strength of expectation between the two training conditions.

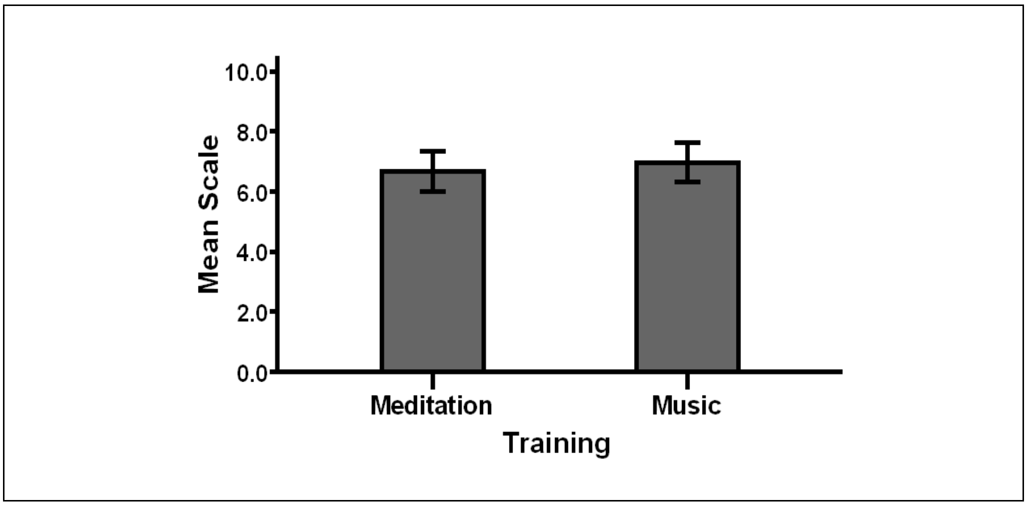


Figure 5.3 Results of norming study measured the expectation on meditation and music trainings to BCI performance. Participants rated on a 1 to 10 scale to show the strength of their expectation on meditation and music trainings to improve BCI performance. Bar chart shows the mean scale of people's expectation on meditation and music trainings. Error bars indicate 95% CI.

Another way of assessing the sensitivity of a non-significant result is with a Bayes factor, which compares a theory that there is an association with the null. For the current data with a 2 x 2 table with cell counts *A*, *B*, *C*, *D*, as presented in Table 5.2, the natural log of the odds ratio is normally distributed with squared standard error (*SE*) that is derived from $1/A + 1/B + 1/C + 1/D$. The log odds ratio obtained was .1495 with a *SE* of .547. The theory of an association was represented by a half normal distribution assuming a "unit information prior" for each of *p(med)* and *p(mus)*. The standard deviation of the half-normal distribution was calculated by assuming one observation worth of knowledge for *p(med)* and one for *p(mus)* (i.e., .5 observations in each cell); that is, the standard deviation was set to 2.828 (the square root of 1/0.5 + 1/0.5 + 1/0.5 + 1/0.5). The Bayes factor calculator gave the value of .24 (Figure 5.4), indicating strong evidence for the null hypothesis.

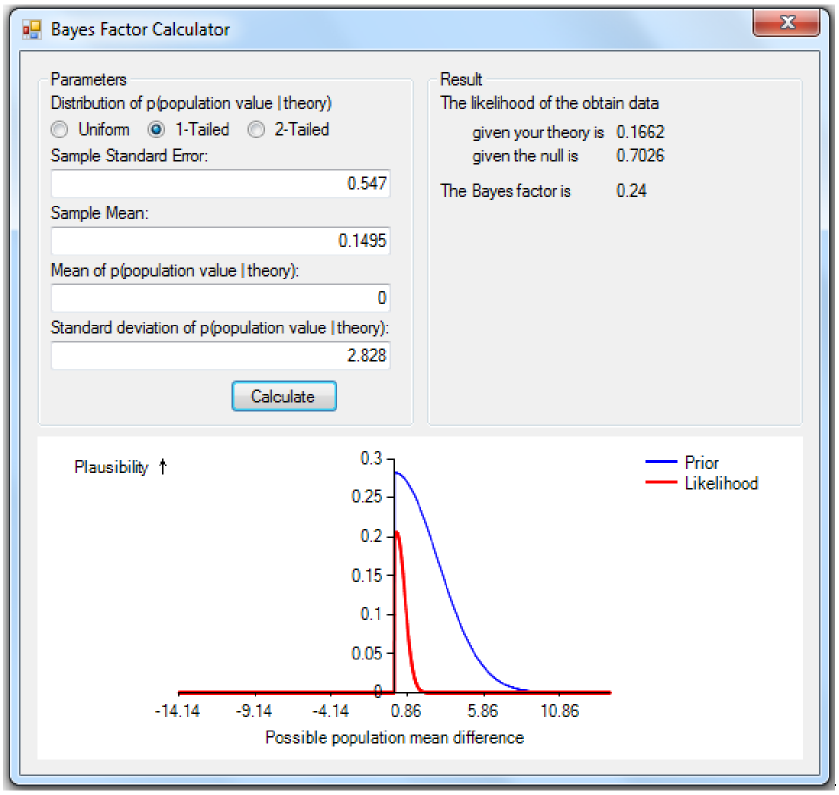


Figure 5.4 Bayes factor calculation for the survey study. The Bayes factor obtained from sample mean .1495, *SE* = .547, in favor of the null hypothesis against the experimental hypothesis (represented by a half normal distribution with mean 0 and standard deviation 2.828 is .24.

5.3 Results of the main study

Originally 32 participants were recruited into the main study. Eight participants dropped out of the study at different times. Twenty-four participants completed the study, $n = 8$ in each group. The completers' age ranged between 18 and 22 years old ($M = 19.75$; $SD = 1.05$). Means and standard deviations of the BCI accuracy scores across the three groups at baseline and post-test are presented in Table 5.3.

One-way analysis of variance (ANOVA) test did not show a significant difference on the baseline BCI accuracy for the three groups, $F(2,21) = .682$, $p = .516$ (see Table 5.4).

One-way analysis of covariance (ANCOVA) using baseline BCI accuracy as covariate showed that the covariate was not significantly related to the baseline BCI scores, $F(1,20) = .296$, $p = .59$ (Table 5.5). The between-group effect was also not significant, $F(2,20) = 1.164$, $p = .33$.

Table 5.3 Mean (standard deviation) of BCI accuracy measured at baseline and after 12-week intervention for meditation, music, and control groups (24 completers).

	n	Baseline	After 12-week	Score Change	*t*	*p*
Meditation	8	.613 (.082)	.597 (.052)	- .016 (.104)	.445	.670
Music	8	.564 (.074)	.575 (.075)	.011 (.112)	- .279	.788
Control	8	.603 (.108)	.533 (.114)	- .070 (.128)	1.550	.165

Note: Within group comparisons using paired-samples t-test did not detect a significant effect for any of the groups, 95% CI [-.071, .104], $t(7) = .45$, $p = .67$; 95% CI [-.105, .083], $t(7) = -.28$, $p = .79$; and 95% CI [-.037, .177], $t(7) = 1.55$, $p = .17$ for meditation, music, and control groups respectively.

Table 5.4 SPSS output of ANOVA test on baseline BCI accuracy (24 completers).

ANOVA

Baseline_accurracy

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.011	2	.005	.682	.516
Within Groups	.167	21	.008		
Total	.178	23			

Table 5.5 SPSS output of ANCOVA test on post-test BCI accuracy using baseline score as covariate (24 completers).

Tests of Between-Subjects Effects

Dependent Variable: Posttest_accuracy

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	.019[a]	3	.006	.872	.472	.116
Intercept	.117	1	.117	15.795	.001	.441
Baseline_accurracy	.002	1	.002	.296	.592	.015
Group	.017	2	.009	1.164	.332	.104
Error	.148	20	.007			
Total	7.925	24				
Corrected Total	.167	23				

a. R Squared = .116 (Adjusted R Squared = -.017)

A Bayesian analysis on the adjusted values of group means of post-test BCI accuracy (obtained from the ANCOVA analysis) was then used to access the sensitivity of the experiment. Given that the purpose of the study was to compare the effect of meditation training to the no-treatment control as well as the active control, the alternative hypothesis (prior) was set-up with the assumption that the effect of meditation compared to no-treatment control is larger than the effect of meditation compared to the active control. A uniform distribution from 0 to .063 (mean difference between the meditation and control is .063) was used. For a sample difference between meditation and music of .016 with *SE* .044, the Bayes factor is .93 (Figure 5.5), which is close to 1, indicating that the test is insensitive and the result did not support either the null or alternative hypothesis. Therefore, to gain more sensitivity in distinguishing the groups, another run involving 44 participants was held the following year.

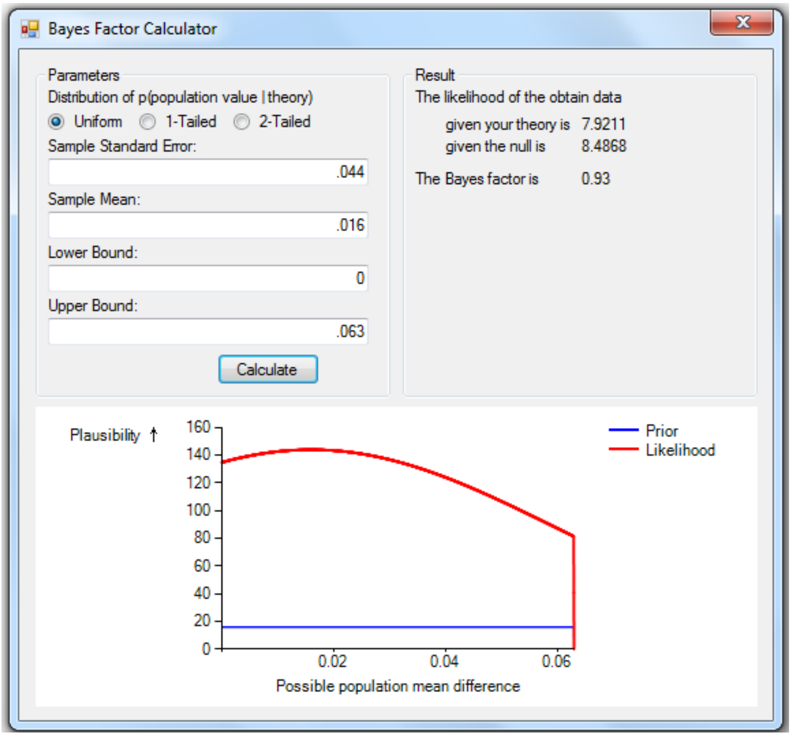


Figure 5.5 Bayes factor calculation for the BCI study based on data from 24 completers. The Bayes factor calculated is .93.

Based now on a total of 76 participants who started, the participant flow is shown in Figure 5.6. The participant were randomized to either mindfulness meditation training, music training, or a no-treatment control group. Thirteen participants dropped out of the study. The reasons given for dropping out were problems in attending the weekly training sessions or the post-tests due to busy personal schedules and inability to continue to commit to the study.

The remaining participants consisting of 23 in the mindfulness meditation group, 20 in the music training group, and 20 in the control group completed the post-test. All were Chinese undergraduates with 58 males and 5 females (2 in the meditation training group, 1 in the music training group, and 2 in the control group) majoring in various engineering courses. Their age ranged between 18 and 24 years old (M = 20.10; SD = 1.52) and self-identified as Buddhists (n = 56), Christian (n = 4), free thinker (n = 2) and a Chinese folk religion follower (n = 1). Fifty-nine were right-handed and four were left-handed.

Means and standard deviations of the BCI accuracy scores across the three groups at baseline and post-test are presented in Table 5.6.

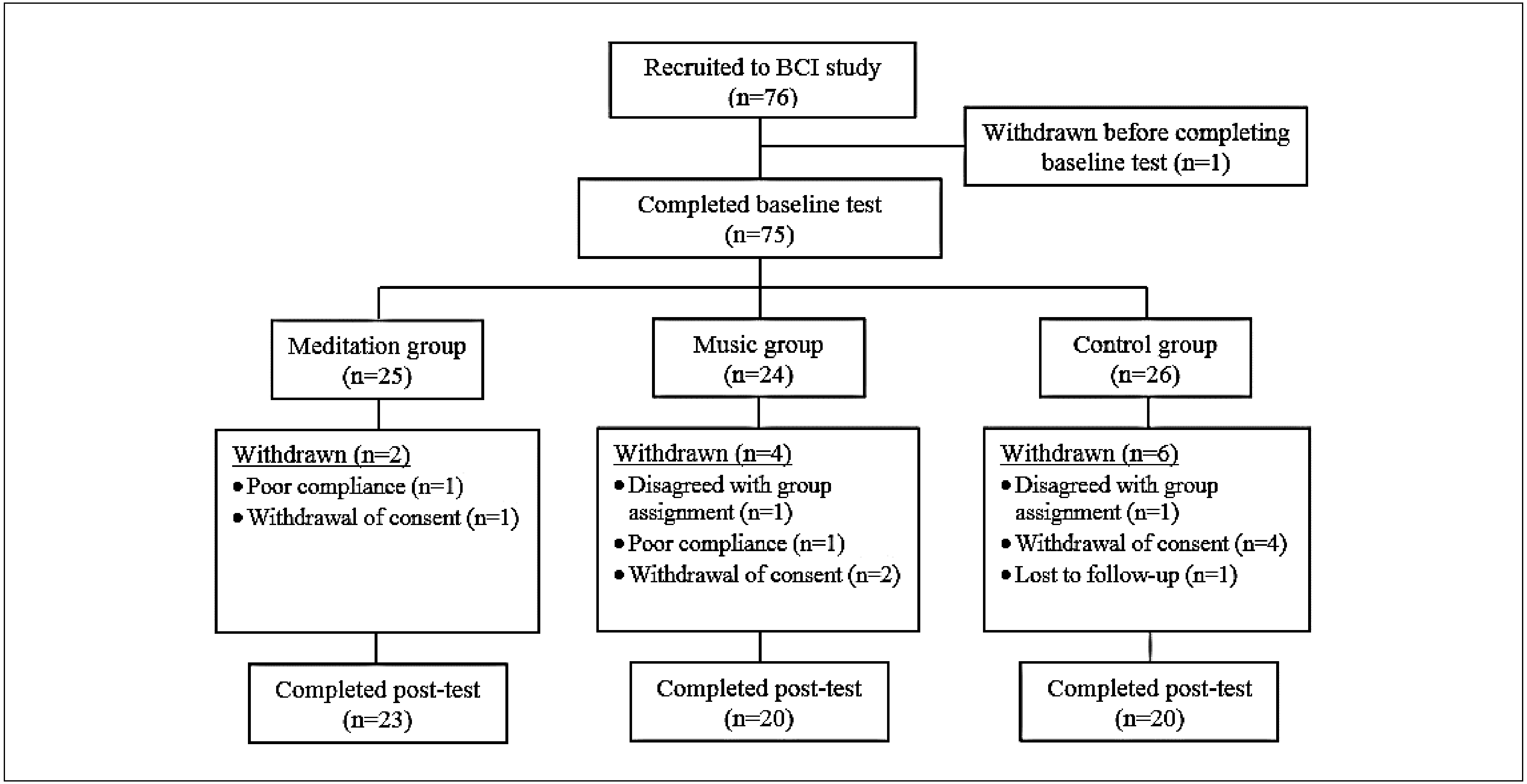


Figure 5.6 Study flow chart showing number of participants recruited, randomized, withdrawn, and completed the post-test.

Table 5.6 Mean (standard deviation) of BCI accuracy measured at baseline and after 12-week intervention for meditation, music, and control groups (63 completers).

	n	Baseline	After 12-week	Score Change	*t*	*p*
Meditation	23	.580 (.081)	.640 (.095)	.060 (.125)	- 2.279	.033*
Music	20	.619 (.100)	.549 (.142)	- .070 (.200)	1.568	.133
Control	20	.564 (.119)	.520 (.104)	- .044 (.143)	1.361	.190

* $p < .05$

Note: The participants who underwent meditation training improved their BCI accuracy significantly, $t(22) = -2.28$, $p < .05$, $r = .44$ while both the music training and no-treatment control groups had poorer BCI accuracy at the post-test compared to their baseline scores but the effects were not statistically significant: $t(19) = 1.57$, $p = .13$ and $t(19) = 1.36$, $p = .19$ respectively.

Table 5.7 SPSS output of ANOVA test on baseline BCI accuracy (63 completers).

ANOVA

Baseline_accurracy

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.032	2	.016	1.577	.215
Within Groups	.604	60	.010		
Total	.635	62			

An ANOVA was conducted on baseline BCI accuracy between the participants from the three groups (Table 5.7). In general, the music training group had a slightly higher mean value of BCI accuracy compared to the other two groups but the ANOVA test did not show a significant difference on the baseline BCI accuracy for the three groups, $F(2,60) = 1.577$, $p = .215$.

An ANCOVA was conducted to compare the between-group effect on the post-test BCI accuracy, with baseline BCI scores as covariate. Results of ANCOVA indicated that the covariate, baseline BCI accuracy was not significantly related to the post-test BCI scores, $F(1,59) = .29$, $p = .60$. There was a significant between-group effect (Figure 5.7) after controlling for the effect of the covariate, $F(2,59) = 6.30$, $p < .005$. The SPSS outputs of ANCOVA test is displayed in Table 5.8.

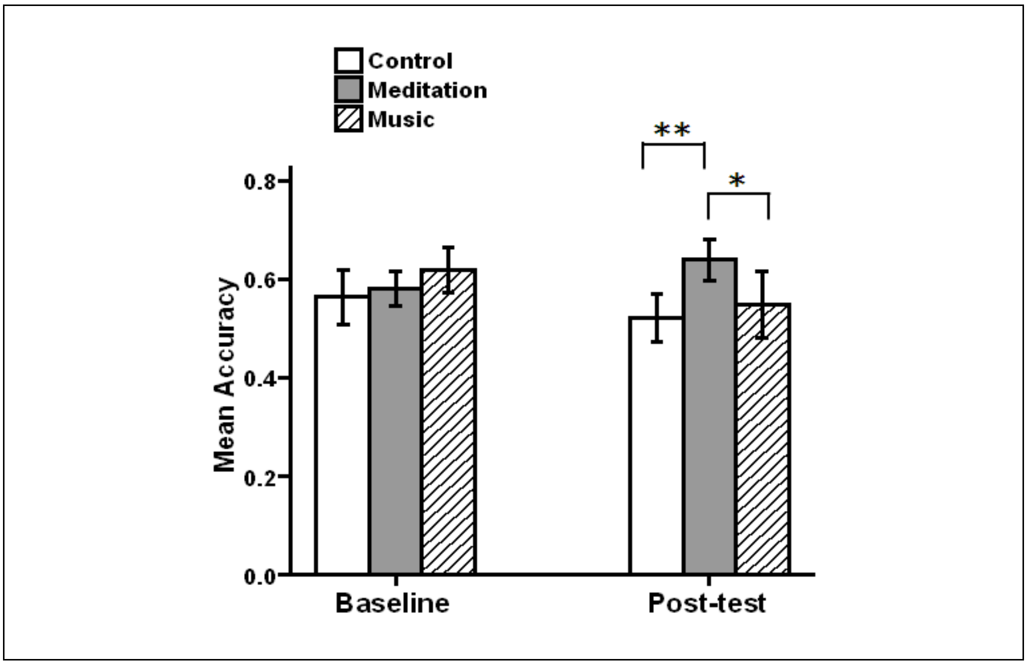


Figure 5.7 Comparisons of BCI accuracy between meditation group, music group, and control group at baseline and after intervention.
* $p < .05$, ** $p < .01$. Error Bars indicate 95% CI.

Table 5.8 SPSS output of ANCOVA test on post-test BCI accuracy using baseline score as covariate: (a) between group-effects (b) post-hoc comparisons.

(a)

Tests of Between-Subjects Effects

Dependent Variable: Posttest_accuracy

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	.172[a]	3	.057	4.300	.008	.179
Intercept	.646	1	.646	48.355	.000	.450
Baseline_accurracy	.004	1	.004	.285	.595	.005
Group	.168	2	.084	6.301	.003	.176
Error	.788	59	.013			
Total	21.651	63				
Corrected Total	.961	62				

a. R Squared = .179 (Adjusted R Squared = .138)

Table 5.8 SPSS output of ANCOVA test on post-test BCI accuracy using baseline score as covariate: (a) between group-effects (b) post-hoc comparisons. (continued)

(b)

Pairwise Comparisons

Dependent Variable: Posttest_accuracy

(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Meditation	Music	.088*	.036	.017	.016	.159
	Control	.120*	.035	.001	.049	.191
Music	Meditation	-.088*	.036	.017	-.159	-.016
	Control	.032	.037	.390	-.043	.107
Control	Meditation	-.120*	.035	.001	-.191	-.049
	Music	-.032	.037	.390	-.107	.043

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments) followed by sequential Bonferroni procedure.

Post-hoc comparisons (Table 5.8(b)) showed that the participants who underwent the meditation training (M = .64, SD =.10) had significantly higher BCI accuracy scores than no-treatment controls (M = .52, SD = .10), $t(59) = 3.39$, $p < .005$, $r = .40$ and the participants who underwent music training (M = .55, SD = .14), $t(59) = 2.45$, $p < .05/2$, after controlling Type I error using sequential Bonferroni procedure, $r = .30$. Participants who underwent the music training did not perform any better than the controls, (95% CI [- .043, .107], $t(59) = .87$, $p = .39$), though the data are consistent with the music group being better than the control group by up to 10%.

A Bayes factor calculation was conducted on the difference between meditation training and music training; this difference, should it exist, was presumed to be plausibly no larger than the difference between meditation training and passive control (a difference of .12). Thus to represent the alternative hypothesis (of a difference between meditation and music), a uniform distribution was used between 0 and .12. The Bayes factor for a sample difference between meditation and music of .09 with a SE of .037 was 11.67 (output of calculation shown in Figure 5.8), which is greater than 3 and indicates strong evidence for the alternative hypothesis over the null hypothesis.

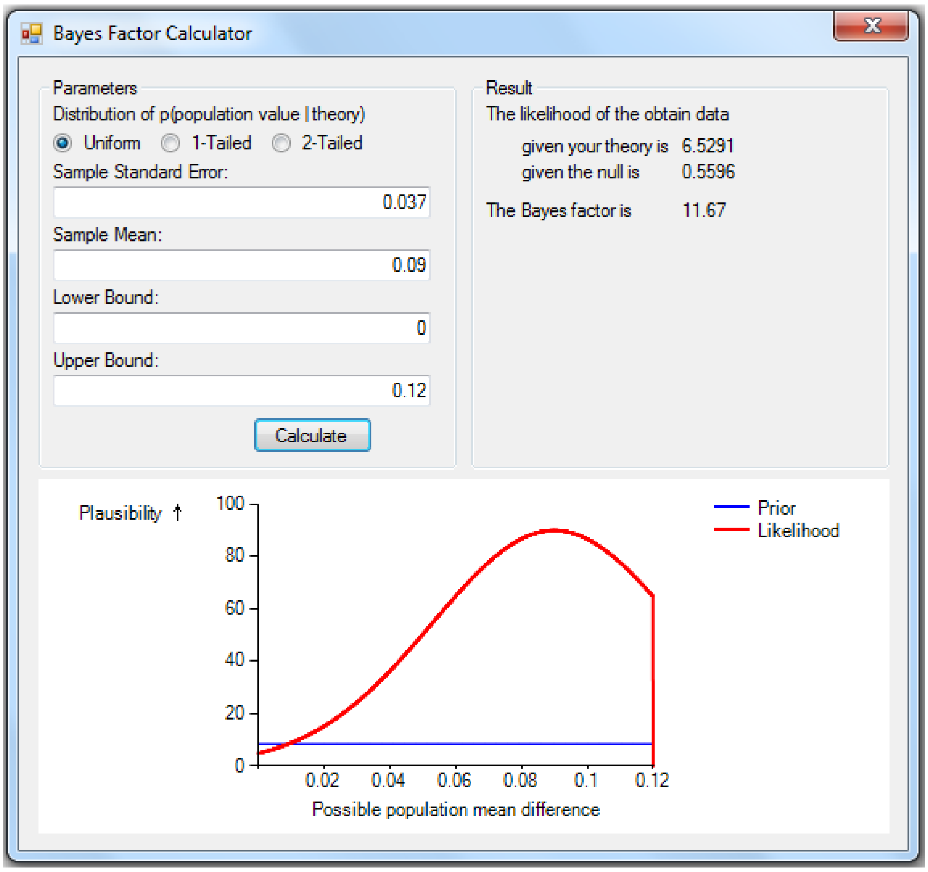


Figure 5.8 Bayes factor calculation for the difference between meditation training and music training. The Bayes factor obtained from sample mean .09, *SE* = .037, in favor of the experimental hypothesis (represented by a uniform distribution between 0 and .12) against the null hypothesis is 11.67.

On the other hand, Bayes factor was calculated on the contrast between music training and control (with sample mean difference of .032 with a *SE* of .037). The alternative hypothesis predicted that the contrast, should it exist, would be equal to or smaller than the contrast between meditation training and control (which is represented by a uniform distribution between 0 and .12). The Bayes factor calculated is .90 (Figure 5.9), which provided very weak evidence for the null hypothesis over the alternative one. In other words, the contrast between music and control was not sensitively detected. This is also implied by the confidence interval (95% CI of the contrast between music and control is

[- .043, .107]), where both the zero value and the interesting difference value were contained within the interval.

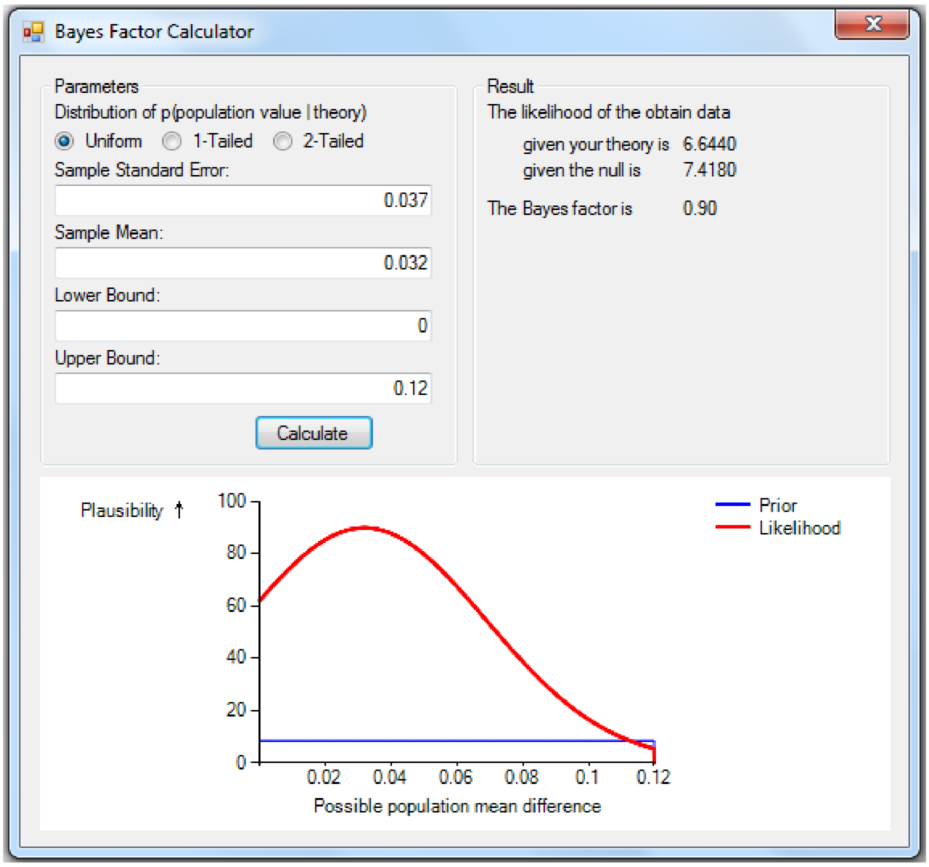


Figure 5.9 Bayes factor calculation for the difference between music training and control. The Bayes factor obtained from sample mean .032, *SE* = .037, in favor of the null hypothesis against the experimental hypothesis (represented by a uniform distribution between 0 and .12) is .90.

CHAPTER 6

DISCUSSION

6.1 Discussion

The study had demonstrated the Bayes factor calculations based on the experimental hypotheses represented by a half-normal distribution (in the survey study) and a uniform distribution (in the BCI study). It is to point out that in the analysis of the survey study, the prior distribution was represented by a half normal scaled distribution assuming a "unit information prior" for each of *p(med)* and *p(mus)*. This assumption is arbitrary but the equivalent of one unit of information is often used as a default for the variance of Bayesian priors in the absence of any other relevant knowledge (see e.g. Kass and Raftery, 1995). In this case the prior amounts to assuming that if there was an association between expectation and training method, in our ignorance we are 95% sure that the odds are between a vanishingly small amount above 1 (no association) up to as large as $exp(2*2.828) = 286$, i.e., *p(med)* about 0.95 and *p(mus)* about .05. The distribution thus reflects our ignorance about the true value of the odds, but allowing for a wide range, while effectively ruling out very extreme values; it also indicates that odds closer to 1 are more likely than larger values, consistent with the prior notion that music and meditation would both be plausible training methods. The relevance of this calculated Bayes factor needs to be taken only provisionally as the theory was determined not by relevant data but an arbitrary default (Dienes, 2008). Contrast this with Rouder et al. (2009) who argue for use of default priors. The relevant data for fixing an adequate theory would be those indicating the relation between expectation and BCI performance, which could be used to determine for the BCI improvements and see what expectation differences would be required to account for that difference. Unfortunately we do not have those data because the participants in BCI study were independent from those who participated in the survey study even though both samples were recruited from the same campus and had a high degree of similarity in the demographic characteristics such as age, education level, ratio of genders, and ratio of ethnics. Nonetheless, the confidence intervals for both the categorical and the continuous strength of expectation ratings also demonstrated the equivalence of expectations for meditation and music training to a high degree of sensitivity.

The results of the survey study on 40 participants found 80% of the participants thought meditation would improve BCI performance rather than not and 78% of the participants thought music training would improve BCI performance rather than not. Our conventional statistical and Bayesian analyses confirmed that both meditation and music interventions elicited clear expectations for improvement on the BCI task, with the strength of expectation being closely matched. In the first phase of the main 12-week intervention study on 32 participants, we found that there was no significant change in BCI performance for within and between group comparisons for meditation, music, and control groups. To test for sensitivity, we introduced a Bayesian analysis of the results where the Bayes factor would indicate the relative strength of evidence for the theory over the null. It would give a three-way distinction between difference, equivalence and insensitivity, and also obviated the need to consider the stopping rule, i.e., for the Bayesian analysis, it is perfectly legitimate to top up subjects until sensitivity is reached (Dienes, 2011). The Bayes factor computed from the results of the 32 participants showed that the test is insensitive. Hence an additional 44 participants was recruited the following year to bring the total number of participants to 76. Based on a total of 76 participants, the conventional statistical and Bayesian analysis both showed that the mindfulness meditation training group obtained a significantly higher BCI accuracy compared to both the music training and no-treatment control groups after the intervention. This study has demonstrated a situation where the Bayes factor is especially useful. Note also that the main effect of mindfulness meditation intervention reported is significant by the orthodox methods after correction for double testing, i.e., using .025 as the criterion for a p-value to indicate 5% significance. We have shown that expectations are roughly the same for music and meditation training for enhancing BCI performance. Then we also demonstrated that meditation rather than music training led to superior BCI performance providing strong evidence that the effect of meditation training on BCI performance involves more than an expectancy effect.

The advantage of the meditation over the music group is one of the first demonstrations of the effectiveness of mindfulness meditation in metacognitive regulation above and beyond an expectancy effect. The randomized control setting had ruled out the possibility that the observed treatment effects are caused by pre-existing differences between the samples, i.e., experts versus novices.

Considering that many previous studies on music training found plasticity in brain functions, and learning music must involve training in attentional regulation to some degree (Posner et al., 2008), the advantage of meditation is all the more impressive. But it does raise the question of why meditation was so superior.

A possible explanation is that a 12-week music training intervention may not have been sufficient to result in domain transfers that are related to the skills required for operating a BCI. Previous studies comparing musicians to non-musicians recruited professional musicians. This population began their practice in childhood and thereafter practised intensely for many years. Researchers have suggested that the differences observed between musicians and non-musicians were related to long-term and intensive practice on a musical instrument (Gaser and Schlaug, 2003; Norton et al., 2005) and early commencement of practice (Amunts et al., 1997; Watanabe et al., 2007).

There may be also another explanation. Previous studies have reported that unstable mental states due to anxiety, fatigue, frustration, or loss of concentration can affect BCI performance (Pfurtscheller and Neuper, 2001; Guger et al., 2003). In our current study, the baseline tests were carried out at the beginning of the university semester while the post-tests were carried out towards the end of the semester when the students experienced greater stress as they were required to submit their course assignments, and to prepare for their semester tests and examinations. The stress and anxiety levels experienced by the participants during the period of post-tests may have been higher compared to the period during the baseline tests. On the other hand, mindfulness meditation may have enhanced emotion regulation in a way music training did not. The meditators were taught how to non-judgmentally observe their sensations, thoughts, feelings, emotions, and environmental stimuli. This requires both cognitive processes of attentional self-regulation and consciousness states monitoring (Bishop et al., 2004). Self-regulation is associated with the ability to control the response to stress and unpleasant stimuli, to sustained focused attention, and to the monitoring and interpreting of the mental states (Fonagy and Target, 2002). Such abilities are particularly important for BCI users to remain focused, calm, and produce consistent EEG patterns. Previous studies have suggested that long-term meditation leads to changes in brain regions that are important to both cognitive control and emotional regulation (Lazar et al., 2005; Hölzel et al., 2011). People who underwent a short-term meditation training reported better moods and reduced stress response (Tang et al., 2007).

6.2 Limitation of the study

The current study was not a blind design. The experimenter was aware of the participants' group allocation. Experimenter bias may thus be a possible factor. The participants in the current study were also aware of their group assignment. Of course, it is not possible to blind the participants from their particular group assignment. However, as both intervention groups hold similar expectations for improvement, any discrepancy found between the two groups on the outcome measure may be credited to the effect of the treatment.

Since the study consisted of entirely Malaysian undergraduate students, it thus limits the generalizability of the findings. Replication with a different population will be valuable to explore the impact of the meditation training on other BCI users.

CHAPTER 7

CONCLUSION

7.1 Conclusion

We found in a 12-week intervention study that a mindfulness meditation training group significantly improved their BCI performance compared to a music training group (learning to play a classical guitar) and a no-treatment control group. Both the mindfulness meditation training and music training groups had positive expectation and beliefs of improvement in BCI performance, and the strength of expectation was about the same for both. The results showed that we have eliminated expectancy effects as an explanation of an objective and useful effect of mindfulness meditation.

7.2 Future direction

Future research could disentangle the contributions of attentional and emotional regulation to the ability of mindfulness training to enhance BCI performance. A randomized control trial exploring the effect of mindfulness meditation on BCI performance using concentrative meditation as an active control would show whether the two forms of meditation have a different effect on BCI performance. As explained earlier in the discussion section above, one would expect that mindfulness meditation may have a more useful effect on BCI performance than concentrative meditation because the regulation of stress and anxiety levels associated with mindfulness plays an important role in ensuring consistent EEG patterns required for good BCI performance.

Further studies in the form of a more detailed analysis of the EEG data as described in Section 5.1 may also reveal how mindfulness meditation training causes changes in brain activity that can improve BCI performance.

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APPENDIX A

BIPOLAR EEG CHANNELS USED IN THE STUDY

Brain region	EEG channel	Electrode position
C3	Channel ac_C3 Channel ap_C3 Channel pc_C3	aC3, C3 aC3, pC3 C3, pC3
CZ	Channel ac_CZ Channel ap_CZ Channel pc_CZ	aCZ, CZ aCZ, pCZ CZ, pCZ
C4	Channel ac_C4 Channel ap_C4 Channel pc_C4	aC4, C4 aC4, pC4 C4, pC4

APPENDIX B

COMBINATIONS OF BIPOLAR EEG CHANNELS

No.	Combination	No.	Combination
1.	ac_C3	19.	pc_C3, ac_CZ
2.	ac_C3, ac_C4	20.	pc_C3, ap_CZ
3.	ac_C3, ap_C4	21.	pc_C3, pc_CZ
4.	ac_C3, pc_C4	22.	ac_C4
5.	ac_C3, ac_CZ	23.	ac_C4, ac_CZ
6.	ac_C3, ap_CZ	24.	ac_C4, ap_CZ
7.	ac_C3, pc_CZ	25.	ac_C4, pc_CZ
8.	ap_C3	26.	ap_C4
9.	ap_C3, ac_C4	27.	ap_C4, ac_CZ
10.	ap_C3, ap_C4	28.	ap_C4, ap_CZ
11.	ap_C3, pc_C4	29.	ap_C4, pc_CZ
12.	ap_C3, ac_CZ	30.	pc_C4
13.	ap_C3, ap_CZ	31.	pc_C4, ac_CZ
14.	ap_C3, pc_CZ	32.	pc_C4, ap_CZ
15.	pc_C3	33.	pc_C4, pc_CZ
16.	pc_C3, ac_C4	34.	ac_CZ
17.	pc_C3, ap_C4	35.	ap_CZ
18.	pc_C3, pc_C4	36.	pc_CZ

APPENDIX C

DEMOGRAPHIC FORM

Participation Form
Universiti Tunku Abdul Rahman
Faculty of Engineering & Science
Brain Science Research Group
Project: Effect of Mental Training on BCI Performance

Ref No.:

Name: ____
Gender: (Male/ Female) Ethnic: ____________ Religion: __________
Age: ______ Date of Birth: ____DD____MM______YY
Student ID: ______________ Course: _________________ (Year__Sem__)
Contact No.: _________________ Email: ___________________________
Address: ____
____

Please answer the following questions:

1. What is your native language? _____________________
2. List the language(s) you use in your daily life.

   ____
3. What is your dominant hand? **(Left/ Right/ Ambidextrous)**
4. Do you wear glasses/lenses during reading? **(Yes/ No)**
5. Do you have any history of colour blindness? **(Yes/ No)**
6. Have you ever had a head injury with the loss of consciousness? **(Yes/ No)**
7. Have you ever been diagnosed with a psychological or mental disorder? **(Yes/ No)**
8. Have you ever been diagnosed with a neurological disorder? **(Yes/ No)**
9. Have you ever been diagnosed with an attention deficit? **(Yes/ No)**
10. Have you ever been treated for or thought you might need treatment for an alcohol or drug addiction? **(Yes/ No)**
11. Have you ever had a serious illness, an accident or an operation? **(Yes/ No)**
12. Have you ever had formal or informal meditation practice or mental training? e.g. meditation class, yoga, self-help tapes or books… **(Yes/ No)**

    If "Yes", please describe the activity, the amount of time you spent for this activity (hours per day or per week) in past or current, as well as the length of the activity (e.g. "I practice breathing exercises once a week for 2 hours since January 2005.").

    ____
    ____
    ____

13. Do you practice playing any musical instrument? **(Yes/ No)**

If “Yes”, please describe the activity, the amount of time you spent for this activity (hours per day or per week) in past or current, as well as the length of the activity.

** The eligible participants will be contacted.

APPENDIX D

INFORMED CONSENT

RESEARCH PARTICIPANT INFORMED CONSENT
UniversitiTunku Abdul Rahman
Faculty of Engineering & Science
Brain Science Research Group

I. Title of Study: Effect of Mental Training on BCI Performance

II. Investigator: Ms Tan Lee Fan

III. Purpose of the Study:
The purpose of this study is to investigate the effect of mental training such as meditation and learning a musical instrument on the BCI performance.

IV. Study Procedures:
If you participate in this study, you will undergo the following tasks at the beginning of the study:

a) EEG experiment
An EEG experiment will be carried out to analyze the brain activities of the participants. The investigator will place some sensors on certain locations of your scalp and face. You will undergo a number of trials of mental tasks in a seated position. The duration of the experiment is about 120 minutes including the process of setting up the sensors.

(b) BCI Test
In another laboratory visit, you will have to complete a BCI test. From this test, you will know how well you can control a BCI using your brain waves. Sensors will be placed on your scalp and face also. The whole process of the test is between 60 - 120 minutes depending on the participant's performance.

Tasks (b) will be repeated at 3 months after the beginning of the study.

During the 3-month period, selected participants will be invited to attend a mindfulness meditation programme or a guitar learning programme. Both programmes will be conducted by professional teachers and provided free of charge to the participants.

V. Potential Risks:
There may be some discomfort experienced by attaching the sensors on the scalp and face with electro-gel and secured with stickers. Under rare circumstances, people with very sensitive skin may have some minor irritation or redness on the skin in reaction to the application of electro-gel.
Additionally, because of the duration of the tests and the fact that you are asked to remain as still as possible, some people may find the experiment to be uncomfortable and unpleasant. The investigator will check with you to determine if you are having any such negative sensations.

VI. Benefits:
There will be no direct benefit to you for participating in these brain science experiments but the results of these experiments may lead to understanding of the brain and help to improve the Brain-Computer Interface (BCI) system.

Selected participants will have the opportunity to learn the skills of meditation or skills of playing guitar.

VII. Costs:
All participation fees for meditation class or musical class or any other expenses in the experiments which will be performed as a part of this study are provided at no cost to you.

VIII. Compensation:
You will receive a cash payment of RM25.00 after every test session. Payment will be discontinued if you decide to withdraw your participation.

IX. Alternative:
You may choose not to take part in this study.

X. Confidentiality:
Information obtained for this study will be stored in the investigator's research files and will be identified only by codes instead of the participants' name.
Information gathered in this study may be published or presented in public forums. However your name and other identifying information will not be used or revealed.

XI. Voluntary Participation:
Your decision to take part in this study is entirely voluntary. You may choose to or not to participate in this study. You may also withdraw from this study at any time with any reason, without any penalty.

XII. Questions:
For enquiry please contact the investigator, Ms Tan Lee Fan at:
Mobile: ___________, E-mail: ___________________________,
Office: _____________________________

XIII. Statement of Consent:
I have read and understood the above information. I have had the opportunity to discuss this research study with the investigator, Ms Tan Lee Fan and/or her research partners, and I have had my questions answered by them in a language that I understand. I take part in this study voluntarily, and I understand that I may withdraw my consent and discontinue my participation in this study at any time without any penalty. My consent to participate in this study does not waive any of my legal rights in the event of negligence or carelessness of anyone working on this project. A copy of this consent form has been given to me.

I agree to take part and give full commitment to this study.

Subject's Name:
IC no.: __________________
Date: Signature

Witness's Name:
IC no.: __________________
Date: Signature

Investigator's Name:
IC no.: __________________
Date: Signature

APPENDIX E

DERIVATION OF BAYES FACTOR EQUATION

The Bayes' theorem says that

$$P(H|D) = P(D|H) \times P(H)/P(D) \quad \text{(D.1)}$$

where $P(H)$ is the prior, the probability of one's thought the hypothesis was prior to data collection; $P(H|D)$ is the posterior, the probability of the hypothesis given the data; $P(D|H)$ is the likelihood of the hypothesis, that is the probability of obtaining the data, given one's hypothesis.

In order words, the posterior is proportional to the likelihood times the prior.

$P(H|D)$ is proportional to $P(D|H) \times P(H)$

An experiment usually consists of 2 particular hypotheses, with H_1 is the experimental hypothesis and H_0 is the null. So

$P(H_1|D)$ is propotional to $P(D|H_1) \times P(H_1)$ (D.2)
And $P(H_0|D)$ is propotional to $P(D|H_0) \times P(H_0)$ (D.3)

Dividing (D.2) by (D.3),

$$P(H_1|D)/P(H_0|D) = P(D|H_1)/P(D|H_0) \times P(H_1)/P(H_0)$$

That is

$$Posterior\ odds = likelihood\ ratio \times prior\ odds$$

where the likelihood ratio is called the Bayes factor, B in favor of the experimental hypothesis.

(Dienes, 2008)

APPENDIX F

C# PROGRAM SOURCE CODE FOR BAYES FACTOR CALCULATOR

```
namespaceBayesFactorCalculator
{
classBayesFactor
    {
publicenumPrior { Uniform, OneTailed, TwoTailed };
Prior distribution = Prior.Uniform;
publicdoubleLikelihoodtheory, Likelihoodnull, Bayesfactor;
double area = 0;
double theta = 0;
double sd2 = 0;
double omega = 0;
doubleincr = 0;
doublelowerBound, upperBound;
doublemeanOfTheory;
double obtained;

publicBayesFactor(doubleSampleMean, doubleSampleSD, doubleLowerBound,
doubleUpperBound)
        {
            obtained = SampleMean;
            sd2 = SampleSD * SampleSD;
            theta = LowerBound;
lowerBound = LowerBound;
upperBound = UpperBound;
incr = (UpperBound - LowerBound) / 2000;
        }

publicBayesFactor(doubleSampleMean, doubleSampleSD, doubleTheoryMean,
doubleTheorySD, Prior Distribution)
        {
            obtained = SampleMean;
            sd2 = SampleSD * SampleSD;
meanOfTheory = TheoryMean;
            omega = TheorySD * TheorySD;
            theta = TheoryMean - 5 * Math.Pow(omega, 0.5);
incr = Math.Pow((omega), 0.5) / 200;
            distribution = Distribution;
        }

privatedoubleNormaly(double mean, double variance, double x)
        {
returnMath.Pow(2.718283, (-(x - mean) * (x - mean) / (2 * variance))) /
(Math.Sqrt(2 * Math.PI * variance));
        }

publicList<double>chartX, chartThetaY, chartLikelihoodTheoryY;
publicList<double>chartTheta { get; set; }

publicvoidCalculateBayesFactor()
        {
            area = 0;
```

```
chartX = newList<double>();
chartThetaY = newList<double>();
chartLikelihoodTheoryY = newList<double>();
for (inti = -1000; i<= 1000; i++)
            {
                theta = theta + incr;
chartX.Add(theta);
doubledist_theta = 0;
doubledist_theta_nextstep = 0;
switch (distribution)
                {
casePrior.Uniform:
if (theta >= lowerBound&& theta <= upperBound)
                        {
dist_theta = 1 / (upperBound - lowerBound);
                        }
if (theta + incr>= lowerBound&& theta + incr<= upperBound)
                        {
dist_theta_nextstep = 1 / (upperBound - lowerBound);
                        }
break;
casePrior.OneTailed:
if (theta > 0)
                        {
dist_theta = 2 * Normaly(meanOfTheory, omega, theta);
                        }
if (theta + incr> 0)
                        {
dist_theta_nextstep = 2 * Normaly(meanOfTheory, omega, theta + incr);
                        }
break;
casePrior.TwoTailed:
dist_theta = Normaly(meanOfTheory, omega, theta);
dist_theta_nextstep = Normaly(meanOfTheory, omega, theta+incr);
break;
                }

double height = (dist_theta * Normaly(theta, sd2, obtained) +
dist_theta_nextstep * Normaly(theta + incr, sd2, obtained)) * .5;
                area = area + height * incr;
chartThetaY.Add(dist_theta);
chartLikelihoodTheoryY.Add(height);
            }
Likelihoodtheory = area;
Likelihoodnull = Normaly(0, sd2, obtained);
Bayesfactor = Likelihoodtheory / Likelihoodnull;
        }
    }
}
```