Comparing Brain-Computer Interfaces across varying technology access levels

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Preface

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Table of Contents

Acknowledgements I

Preface II

List of Tables VIII

List of Figures IX

List of Charts X

Glossary of Terms XI

Chapter 1: Introduction 1

1.1 Introduction 1

1.2 Problem Statement 2

1.3 Research Question 3

1.4 Aims 4

1.5 Hypothesis 4

1.6 Methodology 4

1.7 Scope 5

1.8 Limitations 6

1.9 Outline of Dissertation 6

1.10 Summary 7

Chapter 2: Theoretical background 8

2.1 Introduction 8

2.2 Usability 8

2.2.1 Usability Definitions 8

2.2.2 Usability Measurement Models 10

2.2.3 Usability in BCIs 13

2.3 Contributing Factors 13

2.3.1 Computer Anxiety 13

2.3.2 Computer Attitude 14
2.4 Natural User Interface (NUI) 15
2.5 BCI Historical Background 16
2.6 BCI Categories 17
2.6.1 Invasive BCIs 18
2.6.2 Non-invasive BCIs 19
2.7 BCI Techniques 19
2.7.1 Functional Magnetic Resonance Imaging (fMRI) 20
2.7.2 Electroencephalography (EEG) 20
2.8 BCI Signals 23
2.8.1 Slow Cortical Potential (SCPs) BCIs 23
2.8.2 Sensorimotor Rhythm BCIs 25
2.8.3 P300 Evoked Potentials BCIs 27
2.8.4 Steady-State Visual Evoked Potentials (SSVEP) BCIs 29
2.9 Candidate EEG BCI Systems 31
2.9.1 Cyberlink 32
2.9.2 BCI2000 33
2.9.3 Emotiv EPOC 34
2.9.4 General BCI Systems 37
2.10 BCI Robotic Studies 38
2.11 Summary 40
Chapter 3: Research Design and Methodology 41
3.1 Introduction 41
3.2 Research Design 41
3.3 Research Methodology 42
3.3.1 Sampling 43
3.3.2 Data Collection 45

3.3.3 Evaluation Methods 45
3.3.4 Usability Testing 49
3.3.5 Data Analysis 51
3.4 Summary 53
Chapter 4: Experimental Design 54
4.1 Introduction 54
4.2 Hypothesis 54
4.3 Usability Metrics 54
4.3.1 Efficiency 55
4.3.2 Effectiveness 56
4.3.3 Learnability 56
4.3.4 Satisfaction 56
4.4 Determining Groups 57
4.4.1 Measuring Anxiety 57
4.4.2 Expertise Rating 58
4.5 Experiment 58
4.5.1 Task Structure 59
4.5.2 Session 59
4.5.3 Levels 60
4.5.4 Test Course 61
4.5.5 Test Location Descriptions 63
4.6 Test Instrument 64
4.6.1 Software 65
4.6.2 Hardware 67
4.7 Measurements 68
4.7.1 Measuring Efficiency 68
4.7.2 Measuring Effectiveness 69

4.7.3 Measuring Learnability 69
4.7.4 Measuring Satisfaction 69
4.8 Protocol 70
4.8.1 Test Administration Protocol 70
4.8.2 Training Protocol 70
4.8.3 Usability Testing Protocol 70
4.9 Summary 71
Chapter 5: Experiment Analysis 72
5.1 Introduction 72
5.2 Participants 72
5.3 Comparative Analysis of Efficiency 74
5.4 Comparative Analysis of Effectiveness 81
5.5 Participant Satisfaction 87
5.5.1 Satisfaction Analysis 88
5.5.2 Questionnaire Summary 92
5.6 Imagined Movement 92
5.7 Discussion 94
5.8 Summary 95
Chapter 6: Conclusion 96
6.1 Introduction 96
6.2 Motivation 96
6.3 Study Findings 96
6.4 Contribution to the field 99
6.5 Recommendations 99
6.6 Further Research 100
6.7 Summary 101
References 102

Appendix A 125
Appendix B 127
Appendix C 131
Appendix D 132
Appendix E 133
Appendix F 144
Summary 149
Opsomming 151

List of Tables

Table 2.1: Usability definitions in Standards 9
Table 2.2: Quality characteristics of ISO 9126 9
Table 4.1: Task Levels 60
Table 5.1: Computer Anxiety score breakdown 73
Table 5.2: Number of participants per level 74
Table 5.3: Normality tests for Efficiency 75
Table 5.4: Mauchly's tests for Efficiency 76
Table 5.5: Repeated measures ANOVAs usability test results for the six levels 77
Table 5.6: Normality tests for Effectiveness 82
Table 5.7: Mauchly's test for Effectiveness 83
Table 5.8: Repeated measures ANOVAs usability test results for the six levels 84
Table 5.9: Participants overall reaction to the Emotiv 88
Table 5.10: Participants' opinions regarding learning to use the Emotiv 89
Table 5.11: Participants feelings on the capability of the Emotiv 90
Table 5.12: Participants reactions to the acceptability of the Emotiv for navigation 91
Table 5.13: Examples of imagery used for each action 93

List of Figures

Figure 2.1: Classification of Human-Machine Interfaces 17
Figure 2.2: A detailed overview of the brain and limbic system 18
Figure 2.3: A laptop computer and redesigned cap to improve the Wadsworth BCI's portability and ease of use 21
Figure 2.4: A stimulus matrix monitored by a subject 28
Figure 2.5: FRIEND II system 30
Figure 2.6: An early version of the Cyberlink system 32
Figure 2.7: Image of a system utilising the BCI2000 software 33
Figure 2.8: Emotiv EPOC being used in a research study 34
Figure 2.9: Block diagram of a typical BCI 36
Figure 2.10 (a): KT-X PC robot 40
Figure 2.10 (b): NAO H25 robot 40
Figure 2.10 (c): Robotic arm picking up coloured pawns 40
Figure 2.11 (a): Paper with path and goals 40
Figure 2.11 (b): Robot arm drawing path 40
Figure 4.1: A matrix of criteria and factors in the QUIM model 55
Figure 4.2 Two demographic questions from recruitment questionnaire 58
Figure 4.3: Early version of test course 62
Figure 4.4: Test course used for this study 63
Figure 4.5: Application overview 64
Figure 4.6: Emotiv Control panel 65
Figure 4.7: The remote application for the Emotiv 66
Figure 4.8: ERD for database used to capture data 67
Figure 4.9: Pair of Mindstorm NXT robots used for this study 68
Figure 4.10: Error guidelines for Course A 69

List of Charts

Chart 5.1: Mean time taken for level 1 using an Emotiv 77
Chart 5.2: Mean time taken for level 1 using a keyboard 77
Chart 5.3: Mean time taken for level 2 using an Emotiv 78
Chart 5.4: Mean time taken for level 2 using a keyboard 78
Chart 5.5: Mean time taken for level 3 using an Emotiv 78
Chart 5.6: Mean time taken for level 3 using a keyboard 78
Chart 5.7: Mean time taken for level 4 using an Emotiv 78
Chart 5.8: Mean time taken for level 4 using a keyboard 78
Chart 5.9: Mean time taken for level 5 using an Emotiv 79
Chart 5.10: Mean time taken for level 5 using a keyboard 79
Chart 5.11: Mean time taken using the Emotiv on level 6 79
Chart 5.12: Mean time taken using the keyboard on level 6 79
Chart 5.13: Mean time taken to complete a usability test using the Emotiv 80
Chart 5.14: Mean error comparison of level 4 for both control methods 83
Chart 5.15: Mean error rate for level 1 using the Emotiv 85
Chart 5.16: Mean error rate for level 2 using the Emotiv 85
Chart 5.17: Mean error rate for level 3 using the Emotiv 85
Chart 5.18: Mean error rate for level 4 using the Emotiv 85
Chart 5.19: Error rate mean for level 6 using the Emotiv 85
Chart 5.20: Error rate mean for level 6 using the keyboard 85
Chart 5.21: Error rate mean per level using the Emotiv 86
Chart 5.22: Error rate mean per level using the keyboard 86

Glossary of Terms

The acronyms used throughout the thesis are as follows:

ALS - Amyotrophic Lateral Sclerosis

AIDE - semi-Automated Interface Designer and Evaluator model

BCI – Brain Computer Interface

BMI – Brain Machine Interface

BOLD - Blood Oxygen Level Dependent

DRUM - Diagnostic Recorder for Usability Measurement model

EEG – Electroencephalography

EMG - Electromyography

EOG - Electrooculography

fMRI - Functional Magnetic Resonance Imaging

GOMS - Goals, Operators, Methods and Selection rules model

LED – Light-Emitting Diode

MCP Neurons - McCulloch-Pitts Neurons

MEG - Magneto Encephalography

MRI - Magnetic Resonance Imaging

MUSiC - Metrics for Usability Standards in Computing model

NIST - National Institute of Standards and Technology standard

PAF - Peak Alpha Frequency

QUIM - Quality in Use Integrated Measures model

SANe - Skill Acquisition Network model

SCP - Slow Electrical Potentials

SDK – Software Development Kit

SQuaRE - Software Product Quality Requirements and Evaluation

SSVEP - Steady-State Visual Evoked Potentials

Chapter 1: Introduction

1.1 Introduction

Natural User Interfaces (NUIs) are a means for replacing or supplementing traditional input methods (e.g. the mouse and keyboard) with alternative methods of interaction (Ballmer, 2010; Norman, 2010). There are a number of alternative input interfaces available, including eye tracking (cf. Pradeep, Govada and Swamy, 2013), voice recognition (cf. Zumalt, 2013) and Brain Computer Interfaces (BCI) (cf. Cincotti et al., 2008). BCIs in particular offer an innovative alternative and could form a valuable integrated component to NUIs. As such, BCIs will be the focus of the current research study.

A BCI is a device that uses neurophysiological signals measured from the brain to activate external machinery (Birbaumer and Cohen, 2007). Traditionally, the foremost application of BCIs was to enhance the standard of living for severely disabled patients (Wolpaw et al., 2002), often in the form of a communication channel or as an input method for a prosthesis. However, these systems are usually designed to assist a few persons with disabilities in a controlled clinical environment, thus requiring a team of skilled researchers to operate them (Muller-Putz and Pfurtscheller, 2008; Sellers and Donchin, 2006; Strehl et al., 2006). This has resulted in a shortage of available data on how BCIs perform with able-bodied persons. According to Nicolas-Alonso and Gomez-Gil (2012) there has been a recent trend in BCI research to investigate how a BCI performs for able users. However, these studies are still too few to make a substantial impact and more information is required in this regard (He et al., 2013).

The development of commercially available BCIs (Emotiv, n.d.) has enabled this study to attempt to contribute towards the available data by comparing the performance of able-bodied participants when using two input methods, namely a BCI and a keyboard to navigate a robot. The participants will be classified based on their varying exposure to traditional input methods as measured by a questionnaire. The study’s results, in terms of the usability metrics efficiency, effectiveness, learnability and satisfaction, which were derived from a usability model (Section 2.2.2.1), will indicate whether exposure to a traditional input method is a significant factor in performance and will give insight into the usability of a BCI for the participants.

Specifically, if it could be proven that the exposure to traditional input methods has no effect on the adoption of a BCI as an alternative method of interaction, the use of the BCI can be labelled as being intuitive. Thus, with an intuitive interface, a user would require no prior knowledge of how to use a computer, which would be a promising result and indicate that a BCI is suitable for use as a NUI. However, if it is found that exposure to traditional input methods is a requirement for adoption, then methods must be found to make BCIs more accessible to a variety of users. This study will thus determine whether exposure to a traditional input method affects a user's ability to navigate robots using a BCI.

The remainder of this chapter will motivate the necessity for the research, and will then discuss the aims and methodology that are appropriate for this study. The scope of the research will be discussed and finally the limitations of the study will be identified.

1.2 Problem Statement

As previously mentioned, a BCI translates brain activity into a machine-readable command. In practice, a BCI can consist of any technology that can record the brain's activity. There are two types of BCIs, namely invasive and non-invasive BCIs (Section 2.5). The choice of which approach to use is driven by the trade-off between performance and the risk associated with the BCI type. Typically the more invasive the technique, the better the performance, but the higher the risk, due to the need for surgery (Mayaud et al., 2013).

The central goal of BCIs has largely been to serve as an assistive and communication channel for persons with disabilities (He et al., 2013). These include, amongst others, users with Amyotrophic Lateral Sclerosis (ALS) (cf. Birbaumer et al., 1999; Birbaumer, 2006b; Birbaumer and Cohen 2007) and the utilisation of the P300 Speller BCI to provide an extra communication channel for disabled persons (cf. Donchin, 1981; Donchin, Spencer and Wijesinghe, 2000; Sellers and Donchin, 2006). These studies often used specialised, custom-built BCIs that were utilised by a small number of individuals in a controlled clinical setting and required a team of researchers to operate (Schalk, 2004). An investigation by Adams et al. (2008) indicated that the majority of research utilising BCIs aimed to provide communication and control to people with disabilities. Thus, there is a shortage of research on the applications of a BCI for able users. To address this issue, BCI research is needed to supplement human performance when performing demanding tasks or serve as alternative input methods for able users (He et al., 2013).

Based on the keynote speech of Ballmer (2010), it is clear that traditional input methods are being replaced or supplemented by alternative *natural* modes of interaction. These natural modes of interaction have become known as NUIs and have been credited as being more intuitive and thus easier to learn for a user. This study proposes utilising a BCI as an alternative input method to provide direct measurement of the user's mental state and performance while performing tasks similar to wheelchair manipulation. The BCI utilised, the Emotiv (Emotiv, n.d.), was developed by a specialised company that designs commercial BCIs. This BCI was developed for multimedia-oriented applications directed towards the public.

This research intends to investigate whether a BCI's usability is influenced by a user's exposure to a traditional input method. Since the study is well motivated, a research question to address the identified problem must be formulated next.

1.3 Research Question

Scientific research requires a specific problem to be formulated in a way that can be examined clearly by a researcher. Defining the research problem itself involves narrowing down the general interest a researcher has in a field and identifying a problem which is small enough to be investigated (Welman, 2006).

As mentioned previously, this study will compare participants by measuring their performance when using a BCI or a keyboard for robotic control. Since these participants will be categorised according to their exposure to traditional input methods, this could indicate whether a user's background with computers influences their performance. Based on this information, the following research questions were formulated:

- Does a user's exposure to traditional input methods influence a user's performance with a BCI when navigating a robot?
- Does a user's performance with a traditional input method differ from that with a BCI when navigating a robot?
- Does repetitive use of a BCI to navigate a robot improve a user's performance?

The performance of the participants in this study will be determined by measuring the usability of a BCI when performing an action.

The aims for this study can now be extracted from the research questions.

1.4 Aims

The main aim is to investigate the usability of a BCI for robot navigation. The study will investigate whether a user's BCI performance is influenced by his exposure to traditional input methods. Additionally, the study aims to discover whether a user's performance differs when using a keyboard compared to a BCI as well as investigating whether there is improvement of performance in the short term for a user through repetitive use of the BCI.

1.5 Hypothesis

A set of hypotheses was formulated based on the research questions and aims for this research.

- $H_{0,1}$: Exposure to a traditional input method does not influence a user's performance when manoeuvring a robot using a BCI.
- $H_{0,2}$: There is no difference in a user's performance when using a traditional input method, compared to using a BCI when manoeuvring a robot.
- $H_{0,3}$: Repetitive use of a BCI has no effect on user performance when using a BCI.

1.6 Methodology

This study falls under the domain of Human-Computer Interaction (HCI) and performance in the field is generally determined in terms of usability, thus the usability of the BCI will be analysed. For the purpose of this study, usability is defined as "*the capability of the system to be learnable, efficient, effective and satisfying to the user, when used under specified conditions*" (Section 2.2.1). Based on this definition, the *learnability*, *efficiency*, *effectiveness* and *satisfaction* will be analysed. Anxiety will be measured as a means to differentiate further between participants, as computer anxiety could influence performance or the rate of adoption of new technologies.

To compare the usability of a BCI to a keyboard, the participants will be placed into groups based on their predetermined exposure to traditional input methods. Participants will be classified according to their expertise rating with these methods, measured anxiety and their geographical location. A pair of small configurable robots, called Mindstorm NXTs (Mindstorms, n.d.), will be used to navigate a test course, which will be based on the movements common to a motorised wheelchair, a device that is often used in conjunction with a BCI (cf. Li et al., 2013; Stamps and Hamam, 2010; Rebsamen et al., 2007). A pair of robots will be used in one course in order to increase the difficulty of the sessions. The participants will be compared using a BCI and a traditional input method, namely the keyboard, which will serve as the usability baseline.

Data will be collected via usability testing to measure the learnability, efficiency and effectiveness of the BCI when used in this context. Satisfaction will be measured via a questionnaire that will be given to participants at the conclusion of the study. Anxiety will be measured via the established computer anxiety survey by Marcoulides (1989). This questionnaire will be included in the recruitment questionnaire, along with questions to determine a participant's expertise rating and geographical location (Appendix A). The recruitment questionnaire results will be used to determine whether a participant had a low or high exposure to traditional input methods.

In order to measure usability, a test course will be designed to measure the actions required for the control of a BCI-controlled robot. To capture the necessary metrics from the robot a test instrument will be developed to capture the data accurately in real time (Chapter 4). These measurements will be captured into a database for analysis with a statistical software package (Chapter 5).

1.7 Scope

The scope of this study is limited to the effect that exposure to traditional input methods has on the usability of a BCI. The actions that will be tested will focus on actions that are typical to motorised wheelchairs, as it is representative of a common navigation function for BCIs. However, the scope for this study is limited and thus use of an actual motorised wheelchair is not possible. The actions that will therefore be tested are *move forwards*, *move backwards*, *turn right*, *turn left* and *switch*. The switch action will allow for the control of a robot to change focus from one robot to the other, allowing for the control of two robots simultaneously. This action will abstractly represent peripherals that are common to motorised wheelchairs.

This study concentrates on the use of a BCI with movement and will not measure the application of a BCI as a communication channel, as it is beyond the scope of this research. Thus, this study will not concern itself with information rates between the BCI and the traditional input method, but rather the specific usability metrics identified.

1.8 Limitations

Some limitations identified within the scope of the study are:

- The usability of the BCI as an input method and not as a communication channel will be investigated, thus limiting the ability to compare this study with similar BCI research studies.
- Learnability will be measured by repeated usability tests within a small time frame. A longitudinal study would serve as a better measurement of learning.
- Only four usability principles, namely effectiveness, efficiency, learnability and satisfaction, will be measured.

1.9 Outline of Dissertation

In Chapter 1 the proposed study was introduced, the aims of the study determined and the methodology outlined. The chapter closes with a discussion outlining the scope and limitations of this study. Chapter 2 will be a literature review of some of the available literature related to this study in order to provide a comprehensive overview of the area this study is based upon. Chapter 3 will provide a detailed discussion of the research design and methodology on which the experimental design, which will be discussed in Chapter 4, will be based.

Chapter 5 will discuss the analyses and results of usability testing. Chapter 6 discusses the conclusions drawn from this study, ending with the impact of this dissertation and prospective future work.

1.10 Summary

This chapter introduced the research discussed in this dissertation and motivated its relevance.

It was established that there is a need to address the shortcomings of research with BCIs involving able users and that there is a shortage of experimental research available that utilises BCIs. Towards this end, the study aims to determine whether exposure to traditional input methods affects the usability of a BCI with able users, and whether a user's performance differs between the keyboard and the BCI as well as investigating whether there is improvement of performance in the short term. To achieve these aims the usability of the BCI and a keyboard will be measured for participants who will be classified according to their exposure to traditional input methods.

The participants will navigate a test course in order to measure the learnability, efficiency and effectiveness of the BCI. The data will be collected via usability testing and then analysed. This study will contribute to the field by comparing the usability of a BCI to a traditional input method with able users.

The following chapter will discuss extracts from the available literature related to this study to provide a comprehensive view of the area this study was based on.

Chapter 2: Theoretical background

2.1 Introduction

The proposed study was introduced and motivated in the previous chapter. In order for a research study to be valid, it is important for the study to be informed by existing research. This chapter will thus discuss some of the literature related to the proposed study.

As this study intends to compare the usage of a BCI between participants based on their exposure to traditional input methods, usability needs to be defined and related to how it could be applied to the research. Natural User Interfaces (NUIs) are then discussed, followed by an overview of some of the different types of BCIs available, with a focus on BCIs that utilise electroencephalography (EEG) signals. The commercial BCIs considered for use for this research will be discussed and the choice of the Emotiv for this study will then be motivated. Since this study will utilise robotics a brief discussion on studies incorporating BCIs and robotics will be presented.

2.2 Usability

The aims of this study require the measurement and comparison of participant performance while using various input methods to manoeuvre a robot. As mentioned previously, in HCI the performance of an interface is generally determined in terms of usability. Thus, usability needs to be defined and the scientific measuring of usability needs to be discussed.

2.2.1 Usability Definitions

The domain of measurement in science dates back to Churchman (1959). However, the systematic measurement of software quality only appears in more recent studies such as Fenton et al. (1995). The relative infancy of usability helps explain why currently (2013) there is no definitive definition for usability.

The term *usability* refers to a number of different concepts such as execution time, performance, user satisfaction and learnability (Abran et al., 2003). Prior to the International Standard Organisation (ISO), software developers generally defined usability as the attributes of a user interface that made a product easy to use (Bevan, 2009). Attempts were made to standardise the concept of usability, but even so it has not been defined consistently by the standardisation bodies or researchers themselves (Heinermann, Stamer and Sandkuhl, 2013). Table 2.1 illustrates how definitions have changed between the standards from 1998 to 2001.

Table 2.1: Usability definitions in Standards (Abran et al., 2005)

Usability Definitions
(ISO 9241-11, 1998)*: "The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use."*
(IEEE Standard Glossary of Software Engineering Terminology, 1990)*: "The ease with which a user can learn to operate, prepare inputs for, and interpret outputs of a system or component."*
(ISO/IEC 9126-1, 2001)*: "The capability of the software product to be understood, learned, used and attractive to the user, when used under specified conditions."*

The challenge for creating definitions of usability is that it is difficult to specify the characteristic used, as it often depends on the context. Towards this end several different standards and models to measure usability were proposed by the software engineering communities (Seffah et al., 2006), such as the 2002 ISO 9126. This is a set of standards initially published in 1991 and then refined in 2002. The standard represents software quality as a whole set of characteristics that are usable in different contexts (Table 2.2).

Table 2.2: Quality characteristics of ISO 9126 (Seffah et al., 2006)

Internal/External	**Quality-in-use**
Functionality	Safety
Reliability	Satisfaction
Usability	Productivity
Efficiency	Effectiveness
Maintainability	
Portability	

ISO 9126 defined a product-oriented usability approach where usability was seen as an independent factor of software quality that focused on attributes such as the interface

(Abran et al., 2003). This quality model (ISO/IEC 9126-1, 2001, ISO/IEC 9126-2, 2003, ISO/IEC 9126-3, 2003, ISO/IEC 9126-4, 2004) for software products was well known among researchers and has been researched in depth in the software industry (cf. Abran et al., 2005; Nayebi, Desharnais and Abran, 2012; Padayachee, Kotze and Van Der Merwe, 2010). The disadvantages of the standard are as follows (Desharnais, Abran and Suryn, 2011):

- The specific measures that should be used are unclear;
- Overlapping concepts within the standard itself;
- No quality requirements in the standard;
- No guidance on how to assess the measurement results; and
- Ambiguous measurements.

The ISO/IEC 9126-1 (2001) definition is the generally accepted standard and was therefore chosen to serve as the definition for this study. The definition is thus: *"The capability of the software product to be understood, learned, used and attractive to the user, when used under specified conditions."* (ISO/IEC 9126-1, 2001)

As mentioned previously, this definition gives little guidance on how to apply this definition to a usability study. The standard (ISO/IEC 9126-1, 2001) that the definition was extracted from is unclear on what specific measures need to be used. This problem is not unique to this study. Other researchers have attempted to overcome this shortcoming by using different evaluation models, some of which will be discussed in the following section in order to identify a best fit for use with this study.

It should be noted that a more recent (2012) ISO/IEC 2500 SQuaRE (Software Product Quality Requirements and Evaluation) standard has been released (Desharnais, Abran and Suryn, 2011; ISO/IEC 25000, 2005). However, at the time that this study commenced (2010) ISO 9126 was the best-accepted standard available.

2.2.2 Usability Measurement Models

According to Seffah et al. (2006), the most influential models over the last fifteen years include MUSiC, SANe, AIDE, DRUM, GOMS and NIST. These usability models were considered for use in this study before deciding on the Quality in Use Integrated Measures (QUIM model). A brief outline of each model follows.

The Metrics for Usability Standards in Computing (MUSiC) model is concerned with defining measures of software usability which were integrated into the original ISO 9241 standard, but were not well defined (Bevan, 1995; MacLeod et al., 1997). The Skill Acquisition Network (SANe) model concentrates on the analysis of the quality of use of interactive devices using a user interaction model (Bevan and Macleod, 1994). The semi-Automated Interface Designer and Evaluator (AIDE) model provides a tool to evaluate static HTML pages according to predetermined guidelines about web design (Sears, 1995). The Diagnostic Recorder for Usability Measurement (DRUM) is a software tool for analysing user-based evaluations (Macleod and Rengger, 1993). The Goals, Operators, Methods and Selection rules (GOMS) model is used to create usability tasks needed to accomplish a goal within a software system (John and Kieras, 1996) and the National Institute of Standards and Technology (NIST) standard measures web metrics via a set of six computer tools that support rapid, remote and automated testing of website usability (Scholtz and Laskowski, 1998).

These approaches, however, all have three common limitations. Firstly, the models are vague on their definitions of the lower-level usability metrics. For example, there is relatively little information on how to interpret scores from specific quality metrics (Holzinger et al., 2008; Hornbæk and Law, 2007; Seffah et al., 2006). Secondly, the models' standards are static, meaning that none of the models describes the link between phases in the product development cycle and the appropriate usability measures to use (Hyatt and Rosenberg, 1996; Seffah et al., 2006). Thirdly, it is difficult to apply these standards in practice; it is not always clear how usability factors, criteria and metrics defined in the models are related or when a set of metrics is advantageous to use (Holzinger et al., 2008; Seffah et al., 2006).

The QUIM model proposed by Seffah et al. (2006) was designed to solve these shortcomings, as well as to incorporate the strengths from the ISO standards and other influential usability measurement models. However, the model was designed to encompass an entire product life model; therefore, only parts of the model that related to the usability measurements and the guidance given when choosing metrics were used in this study. The model is discussed in detail in the next section.

2.2.2.1 Quality in Use Integrated Measurement (QUIM)

The QUIM model consists of ten factors which correspond to the different facets of existing ISO standards and measurement models (Abran et al., 2003; Seffah and Metzker, 2004; Seffah et al., 2006; Seffah, Gulliksen and Desmarais, 2005). These factors are:

- **Efficiency**: the capability of a system to allow users to expend resources that are appropriate to achieve the task;
- **Effectiveness**: the capability of a user to achieve a task with accuracy and completeness using the system;
- **Productivity**: level of effectiveness achieved in relation to resources consumed;
- **Satisfaction**: a subjective measurement from the users about their feelings when using software;
- **Learnability**: ease with which the system can be mastered by the user;
- **Safety**: whether the system limits the risk of harm to users or other resources;
- **Trustfulness**: the faithfulness a system offers to its users;
- **Accessibility**: the access a system offers to persons with disabilities;
- **Universality**: whether a system accommodates users from different cultural backgrounds; and
- **Usefulness**: whether a system allows users to solve real problems in an acceptable manner.

The model incorporates a number of criteria as possible measurements for usability. Recall that the usability definition chosen to serve as a basis for this study was *"the capability of the software product to be understood, learned, used and attractive to the user, when used under specified conditions"* (ISO/IEC 9126-1, 2001).The keywords of interest are *understood*, *learned*, *used* and *attractive*. *Understood* and *learned* can be measured via the QUIM factor *learnability*. *Used* can be measured by the QUIM factors *efficiency* and *effectiveness*. *Attractive* can be measured by aspects of the factor *satisfaction* (Seffah and Metzker, 2004). The definition can thus be re-written to accommodate the QUIM model as follows: *The capability of the system to be learnable, efficient, effective and satisfying to the user, when used under specified conditions.*

Usability is important for any interface and thus when utilising BCIs. Therefore, the following section will look at the usability of BCIs in detail.

2.2.3 Usability in BCIs

One of the primary uses of BCIs is that it can provide paralysed and able-bodied users with an extra communication channel. For able-bodied users the appeal of BCIs is the privacy offered for communication (Andreassi, 2000). According to Pasqualotto et al. (2011), the technology can also be used as an assistive technology, therefore the usability thereof must be tested in order to avoid dissatisfaction and help promote the use of the technology (Scherer, 2005).

According to Laar et al. (2013), the reliability of a BCI is the most important aspect that needs to be addressed in order to achieve acceptance by the general public. However, if a system is reliable but is not usable, the system will be abandoned. Thus, the usability of a BCI system also needs to be investigated. Studies that measured the usability of a BCI include that of Thulasidas and Guan (2005) who conducted a study using a P300 Speller aimed at optimising the usability of the device. The results of the study indicated that high accuracies could be achieved with training times of as little as ten minutes. A similar study by Li et al. (2010) utilised a P300 Speller and compared two different interfaces and three screen sizes. The results showed that interface type and screen size have significant effects on user performance. Thus, for this study it is important to measure the usability of the BCI in order to verify the devices task performance.

2.3 Contributing Factors

This section discusses computer anxiety and attitude as they could be used to explain observed differences detected between the participants. This relationship could potentially influence the adoption of a NUI such as a BCI.

2.3.1 Computer Anxiety

Computer anxiety is the fear a person has of computers when using a computer or considering the possibility of computer use (Heinssen, Glass and Knight, 1987). Research has shown that there is a correlation between a person's anxiety towards a software package and their usage of that software (Venkatesh, 2000). Furthermore, there is evidence that computer anxiety has an impact on a user's perceived benefit of using a computer and the user's computer competence overall (Bozionelos, 1997; Bradley and Russell, 1997).

A related study showed that differences in computer anxiety between various nations show measurable differences based on the culture of a society (Rosen and Weil, 1995). Similar research has shown that there were even differences among individuals in the same culture and that factors such as gender or background experience may play a role (Broome and Havelka, 2011; McIlroy et al., 2001). Thus, a user's experience with traditional input methods could play a role in the adoption of new technologies.

The relationship between anxiety and background experience was further investigated and it was found that socio-economic factors had a direct positive relationship to computer experience and an indirect negative relationship to computer anxiety. These findings support the principle of the digital divide, which was defined as the inequalities between groups in terms of access and use of information technologies (Bozionelos, 2004).

A more recent study comparing students from a Dutch and a Turkish university indicated that Turkish students had significantly higher levels of computer anxiety. The study additionally specified that the level of computer anxiety dropped significantly the more experience a student had with a computer (Tekinarslan, 2008). These studies have shown that computer anxiety can be used as an indicator of a participant's experience when operating a computer. Additionally, the socio-economic and cultural factor of a participant has been shown to relate to a participant's computer anxiety. Therefore, the measured computer anxiety of a participant can be used to give an indication of a participant's background. In the case of this study the Computer Anxiety Scale (CAS) (Marcoulides, 1989) was thought to be an indicator of an individual's exposure to traditional input methods. The results of the CAS factors are analysed in Section 5.2.

The next section discusses the related concept of computer attitude.

2.3.2 Computer Attitude

An attitude can be described as a positive or negative evaluation of people, objects, events, activities, ideas, or just about anything in one's environment (Fiske, 1998). Attitude has been found to affect a user's performance (Galitz, 2007) and computer experience has been shown to correlate with a person's attitude towards computers (Rezaee et al., 2011; Celik and Yesilyurt, 2013; Loyd and Gressard, 1984b; Orr, Allen and Poindexter, 2001). Thus, it can be said that computer experience could affect a user's performance. Additionally, Loyd and Gressard (1984a) indicated that the attitude participants portray towards computers also corresponds with their feelings of anxiety towards computers. Therefore, if a participant has a negative attitude towards a computer, the user will likely feel anxious while using the device and it will affect his performance.

The measured attitude of participants could be used as an indicator for whether a participant had little experience with computers. In this study, a participant's attitude towards a computer was not directly measured but rather inferred from the results of the CAS questionnaire.

For this research, the BCI is being considered as a viable alternative to traditional input methods for robot navigation. Thus, the usability of a NUI must be investigated and is discussed in the following section.

2.4 Natural User Interface (NUI)

NUIs research involves investigating the replacement or supplementing of traditional input methods with alternative *natural* modes of interaction (Ballmer, 2010; Norman, 2010). NUIs are closely related to multimodal interaction (MMI), which deals with combining multiple modalities in order to provide a flexible, adaptable and natural interface (Gürkök and Nijholt, 2012).

Currently the most popular NUI is where the mouse and keyboard are replaced by touch- and motion- based inputs. Touch interfaces have become readily available to the general public as devices such as tablets (Apple - iPad, n.d.), and touch-enabled phones have become ubiquitous with mobile computing. Touch interfaces have evolved to utilise virtual reality (VR) and interactive touch tables as a method of data visualisation (Keefe and Laidlaw, 2013). It also exploits the mobile multi-touch capabilities to explore data on large high-resolution displays visually. Examples of motion-based alternatives include incorporation of the Microsoft Kinect (Kinect, n.d.) for control interfaces.

A BCI could be considered as a valuable supplementary interface for NUIs; thus, this study will approach the usability of a BCI as a candidate for a NUI.

2.5 BCI Historical Background

> *A brain-computer interface (BCI), also known as a brain-machine interface (BMI), is defined as a device that uses neurophysiological signals that are measured from the brain to activate external machinery* (Birbaumer and Cohen, 2007, p. 621).

Hans Berger (1929) was among the first scientists to discover that a human brain produces an electric signal along the scalp that is machine readable. This electric signal became known as an electroencephalography (EEG) signal. Vidal (1973) was the first scientist, while working with 'The Brain Computer Interface project', who attempted to evaluate the feasibility of utilising the electrical signal produced by the human brain. He subsequently invented the BCI. A variety of techniques has been created to enable scientists to monitor brain activity. Some of the best-known methods include EEG, magneto encephalography (MEG) and functional magnetic resonance imaging (fMRI). Aside from EEG-based techniques, the other approaches are plagued with constraints such as low response times and expensive technical architectural requirements (Wolpaw et al., 2002).

Pioneering studies in BCIs include research into the operant training of single-neuron spike trains by Fetz (1969) and studies of EEG alpha waves by Kamiya (1971). EEGs reflect brain activity and therefore a person's intent can be extracted from these readings. However, the reliability and resolution of the readings that could be extracted in these past studies were limited by the available technology at the time (Wolpaw et al., 2002).

Initially, EEG was mainly used to evaluate neurological disorders in a clinical setting. Thereafter, scientists became interested in investigating brain function in a laboratory setting. The foremost application of BCIs was for the benefit of severely disabled patients to enhance their standard of living (Wolpaw et al., 2002). A number of researchers have explored the therapeutic properties of EEGs (cf. Elbert, Rockstroh, Lutzenberger and Birbaumer, 1980; Kuhlman, 1978; Travis, Kondo and Knott, 1975; Wolpaw et al., 2002). For example, EEG was used to diminish generalised anxiety by increasing and decreasing EEG alpha waves in a participant (Rice, Blanchard and Purcell, 1993). Significant reductions in heart rate indicated a diminishing of general anxiety through reduced reaction to stressors. A shortcoming of the research was that it was performed over a one-month period. It would be beneficial to measure whether the technique could have any long-lasting positive or negative effects on participants.

Up to this point BCI research has been characterised by a focus on methodological and experimental approaches for the restoration of communication (Birbaumer, 2006a; Mak et al., 2012). The scope of this study precludes the restoration of communication but rather uses the BCI as an additional communication channel for navigation. The two categories of BCIs will be discussed in the next section.

2.6 BCI Categories

Figure 2.1 demonstrates how BCIs are commonly categorised by researchers and will serve as a roadmap for the following discussion, starting with the history of BCI development. Wolpaw and Wolpaw (2012) have categorised EEG BCIs into two broad areas, namely invasive BCIs and non-invasive BCIs (Figure 2.1). These categories are discussed in detail in the two following sections.

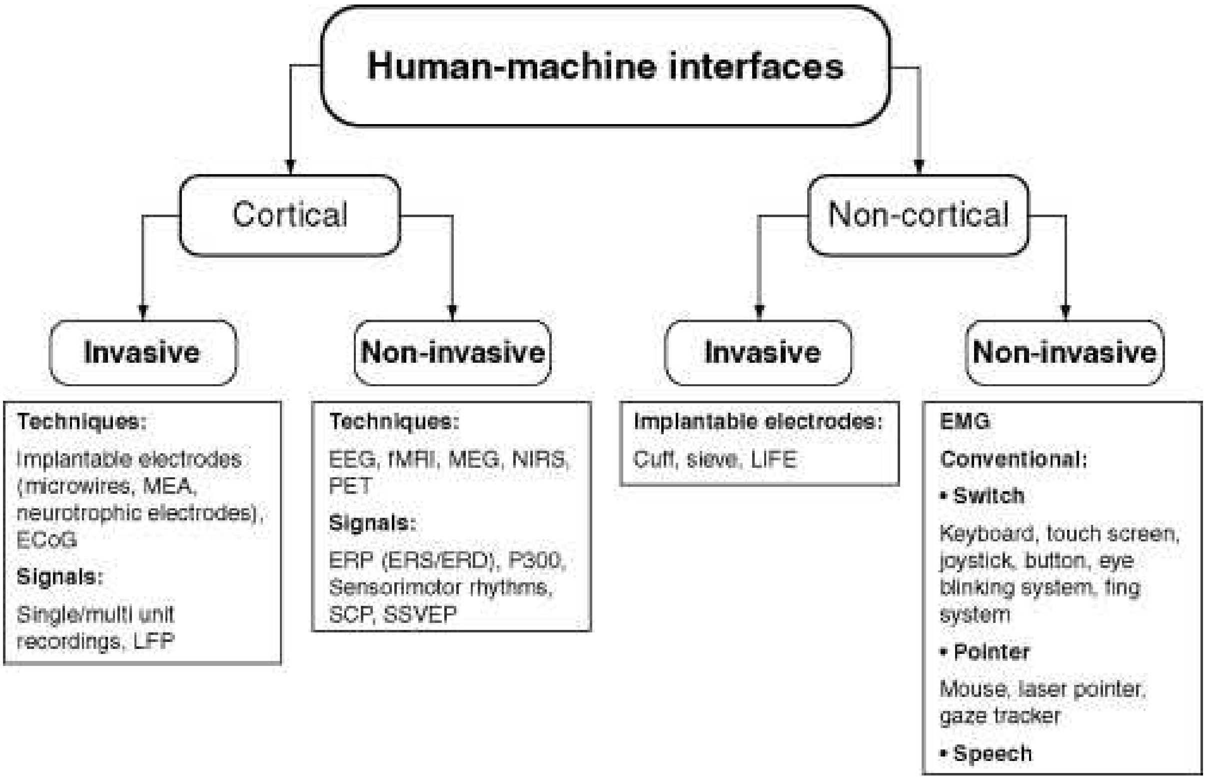


Figure 2.1: Classification of Human-Machine Interfaces (Citi et al., 2009)

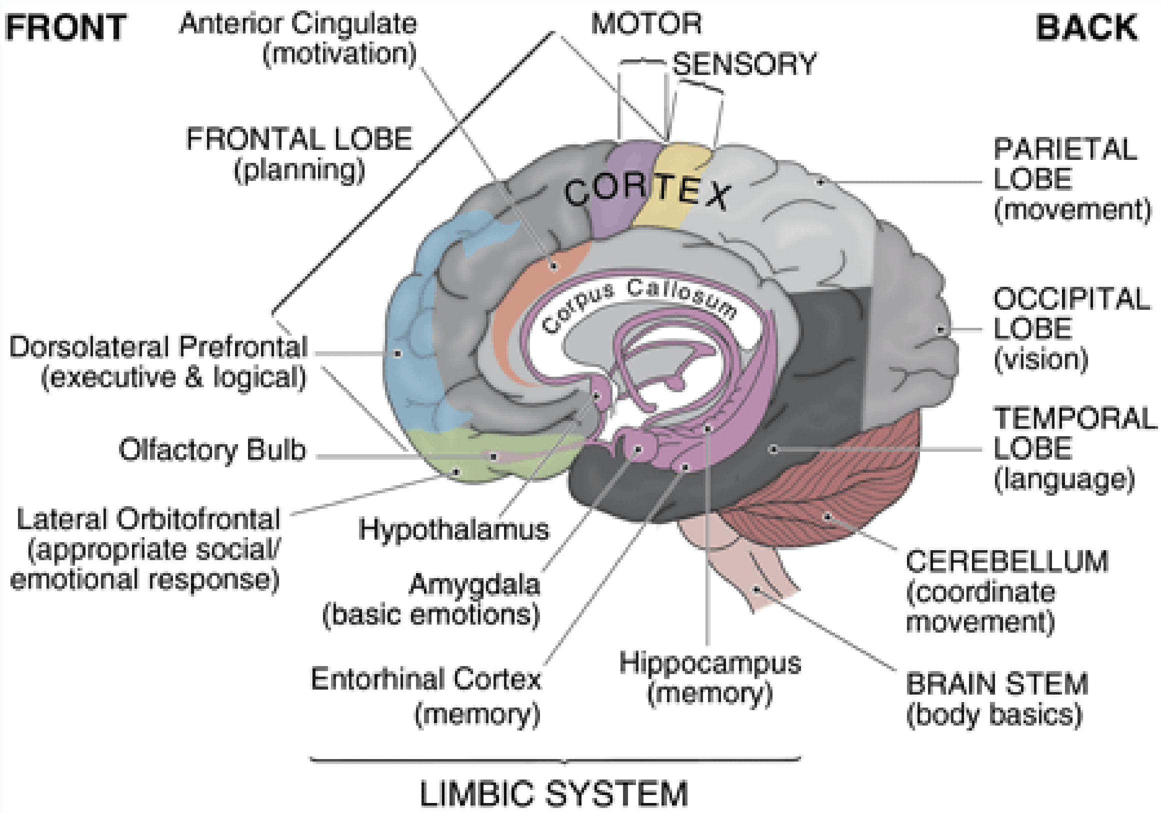


Figure 2.2: A detailed overview of the brain and limbic system (The Brain, n.d.)

2.6.1 Invasive BCIs

Invasive BCIs read neurophysiological rhythms by using electrode sites implanted inside the scalp of the subject. There are three main insertion sites: multi-electrode grids placed in the motor cortex (Figure 2.2; Donoghue, 2002); sensors placed in the premotor cortex (Carmena et al., 2003); or parietal motor areas of subjects (Birbaumer, 2006b; Schwartz, Taylor and Tillery, 2001). Sensors can be placed in one site or any combination thereof, depending on the needs of the individual.

In one of the first studies that showed the potential of BCIs to detect EEG signals with invasive techniques, monkeys were successfully taught to move a virtual cursor across a computer screen (Nicolelis, 2003). A more involved experiment by Hochberg et al. (2006) implanted an array of electrodes into two quadriplegic patients' brains at their hand representation areas in order to measure spike and field potentials. Results showed that with just a few training sessions the patients successfully learnt to move a cursor on a computer screen in several directions. While results were promising, the small specific data sample makes it impossible to draw any strong conclusions from or to generalise the results to a larger population. Despite these weaknesses, the study did show the potential of invasive BCIs as a communication channel.

Aside from being used for control signals, research has shown that invasive BCIs can be used successfully as a treatment regime in humans. Sterman (1977) demonstrated seizure reduction and complete remission in a sample of patients who were inflicted with drug-resistant epilepsy.

Invasive BCIs can clearly be used as an effective communication method. However, from approximately 1980, BCIs were applied using a non-invasive approach, with an invasive setup only being used as a last resort because of the dangers inherent to neural surgery (Wellmer et al., 2012). This trend, together with the associated dangers, the expertise required and resources involved disallowed the use of an invasive BCI for this study.

2.6.2 Non-invasive BCIs

Contrary to invasive BCIs, non-invasive BCIs do not require any surgery, as the electrode sites are placed on the scalp of the participant (Birbaumer and Cohen, 2007). The signals received are interpreted by a computer into a series of control signals which are implemented by a machine of some kind (Minnery and Fine, 2009).

Researchers such as Birbaumer and Cohen (2007) and Wolpaw (2007) believe a non-invasive BCI is a technology that can be improved to a usable level for healthy as well as for disadvantaged individuals. Non-invasive EEG BCIs have a wider appeal to the general populace, examples of commercially available BCIs being the Emotiv (Emotiv, n.d.) and the iBrain (NeuroVigil, Inc., n.d.).

2.7 BCI Techniques

Two of the available BCI techniques will be discussed with emphasis on non-invasive devices that utilise EEG.

2.7.1 Functional Magnetic Resonance Imaging (fMRI)

As neurons become activated, they cause local changes in blood flow and oxygenation in the brain. These levels can be imaged by a computer and correlated to neural activity. The functional magnetic resonance imaging (fMRI) works by using clinical Magnetic Resonance Imaging (MRI) to measure these changes in blood levels. Hemodynamic changes (changes in blood pressure) have been found to occur approximately once a second (Baillet, Mosher and Leahy, 2001). The one-second delay, however, can limit the ability of an fMRI to detect the neural changes in a participant. This delay could give the participant a feeling of unresponsiveness towards the system. The interpretation of fMRI data is further complicated by the complex relationship between the blood oxygen level dependent (BOLD) changes detected and the underlying neural activity. BOLD changes in fMRI also do not necessarily correspond one-to-one with the regions of electrical neural activity (Baillet, Mosher and Leahy, 2001). This could result in the BCI reporting false control signals. Additionally, MRIs are large and expensive devices, limiting the use of fMRI as a BCI outside a laboratory setting (Weiskopf et al., 2004). The technology requires a MRI and a room-sized piece of equipment all of which are far too unwieldy to use outside a clinical setting.

Despite these disadvantages, event-related fMRI has allowed scientists to look more closely at brain activity related to memory formation. Research studies using fMRI have shown that changes in neural activity in the prefrontal cortex (Figure 2.2) can be used to predict memory performance in semantic encoding tasks. For example, fMRI feedback makes it possible for a participant to have voluntary control of brain activity (Köhler et al., 2004). A more recent example demonstrated that dynamic brain activity measured under naturalistic conditions could be decoded into a recognisable image by using current fMRI technology (Nishimoto, 2011). However, in neither of these studies did the researchers attempt to minimise the fMRI disadvantages.

In comparison, EEG BCIs are the favoured BCIs for use in research due to their relatively low cost, high temporal resolution and ease of use (Zander and Kothe, 2011). The next section will discuss the EEG technique in detail.

2.7.2 Electroencephalography (EEG)

EEGs measure the scalp potentials of electrical activity in neural cells in a participant's brain (Baillet, Mosher and Leahy, 2001). These EEG waveforms are then interpreted by the computer into a series of actions that are performed by the BCI on any attached machinery (Minnery and Fine, 2009).

EEGs have an estimated information transfer rate of around 5–25 bits of information per minute (Lebedev and Nicolelis, 2006; Wolpaw et al., 2002). This information bit rate is too low to control complicated machinery, such as a prosthetic arm, but is enough to control a messaging programme, or for complex tasks that are not time sensitive, such as asynchronous control of a robotic arm. Thus, an EEG BCI would be suitable for use with this study to control a simple robot.

The most common non-invasive BCI technology used commercially and in research is the EEG BCI. However, the control signals that can be extracted from an EEG device are limited. The high noise component and the low bit rate are also limiting factors for the application of non-invasive BCIs (Koenig, Marti-Lopez and Valdes-Sosa, 2001). The bit rate of a BCI is the commands per minute that can be accomplished by a BCI during use (McFarland et al., 2011).

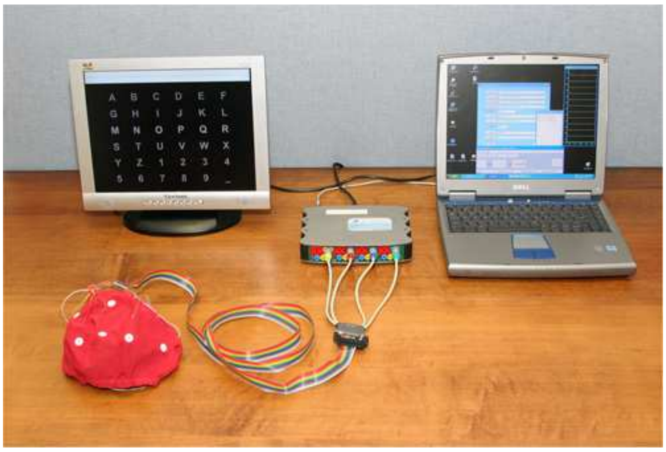


Figure 2.3: A laptop computer and redesigned cap to improve the Wadsworth BCI's portability and ease of use (Wolpaw et al., 2002).

Baillet et al. (2001) believed that EEGs have the potential to have a much better response time, in the order of tens of milliseconds. Towards this goal, basic and clinical research has yielded detailed knowledge of the signals that comprise the EEG (Wolpaw et al., 2002). With this knowledge, researchers have a better understanding of how to leverage EEG signals for command and control. This led to rapid progress in computational technology allowing for sophisticated online analysis of multichannel EEG signals. A promising approach was configuring simple communications such as *Yes* and *No* to serve complex functions, thus minimising one of the core weaknesses of EEG BCI systems. For the proposed study, a complex task such as turning left, which involves a number of motors, can be configured to a single simple command.

One of the major challenges of non-invasive BCIs is the inverse problem. This invokes the difficulties experienced when trying to localise intra-cerebral brain activity from scalp surface recordings taken with a EEG BCI (Koenig, Marti-Lopez and Valdes-Sosa, 2001). These background signals are generally known as signal noise or white noise (Nijholt and Tan, 2008) and are made up of electromyography (EMG), electrooculography (EOG) and mechanical artefacts (Lebedev and Nicolelis, 2006). These difficulties are expressed as unwanted noise detected by the EEG BCI, thus making it difficult for an EEG BCI to detect a command from the participant.

Techniques such as statistical averaging are often used in online and offline BCI systems in an attempt to minimise unwanted EEG signal noise. An online BCI processes the signals in near real time, while an offline system will process the signals after the fact. Anderson et al. (1998) recorded EEG signals from four subjects while they performed two mental tasks to investigate the practicality of using a multivariate autoregressive (AR) model to classify EEG signals. The AR models were found to perform slightly better than the previous averaging techniques. The study only used four participants and results were analysed from only one session limiting the information that could be extracted. A broader study using a larger sample size would be far more valuable. However, the study does demonstrate that noise levels can be minimised or at least reduced. Therefore, once the feasibility of a technique has been proven, measures can be taken to make the technique usable outside the laboratory environment.

In general, the information extracted from an EEG BCI does not match what can be extracted from other BCIs such as fMRI. For example, the resolution of an EEG BCI was found to be limited by the relatively small number of spatial measurements possible with an EEG (Baillet, Mosher and Leahy, 2001). Despite these limitations, EEG BCIs have been shown to be suitable for controlling devices like wheelchairs; hence, suitable to control a robot used for this research. The next step is to identify what type of EEG to use in the study. Before this can be done the different EEG signals that an EEG BCI can detect must be investigated. These are outlined in the following section.

2.8 BCI Signals

EEG signals that can be detected include slow cortical potentials (SCPs), mu, alpha and beta rhythms (sensorimotor rhythms), P300 evoked potentials and Steady-State Visual Evoked Potentials (SSVEP) (Ramirez-Cortes et al., 2011).

SCPs are slow potential variations generated in the cortex (Figure 2.2) of a participant within 0.5–10 seconds. Negative SCPs are associated with movement, while positive SCPs are associated with reduced cortical activation (Bashashati et al., 2007).

The rhythms commonly detectable by BCIs are alpha, beta and mu rhythms. Alpha rhythms are measured from between 8 Hz to 13 Hz; beta rhythms are observed from 12 Hz to 30 Hz and mu rhythms are measured from 8 Hz to 12 Hz (Bashashati et al., 2007; Jasper and Penfield, 1949).

A P300-evoked potential is the positive peak signal generated in the brain approximately 300 milliseconds after a response to target stimuli that occurred unexpectedly for the participant. This stimulus can be visual or auditory, as long as it is unexpected to the participant it will generate a P300 signal (Bashashati et al., 2007; Ramirez-Cortes et al., 2011).

SSVEPs are natural responses produced in the brain to visual stimulations at specific frequencies ranging from 3.5 Hz to 75 Hz. The signal generated is the same frequency as the visual stimulus (Beverina et al., 2003).

BCIs that utilise the specific signals are discussed in the following section.

2.8.1 Slow Cortical Potential (SCPs) BCIs

SCPs measure the shift in cortical potential consciously generated by a participant. The signals reflect changes in cortical polarisation of an EEG lasting between 300 ms and several seconds (Bashashati et al., 2007; Elbert et al., 1980; Wolpaw et al., 2002). Birbaumer (1999) has indicated that humans could learn to regulate SCPs voluntarily after in-depth operant training that uses immediate feedback and positive reinforcement.

SCP BCIs were investigated as a possible solution for locked-in patients to use as a communication tool with the outside world. With an SCP BCI, a patient was able to write a coherent letter by the conclusion of the study. Unfortunately, the time it took the patient to write the letter was 16 hours, a result of the slow bits per minute an SCP BCI is capable of.

Despite the time required, the patient found the experience to be highly rewarding (Birbaumer, 1999). Although the study was successful, the time it takes an SCP BCI to complete a task is unsuitable for use with this study.

Birbaumer's research in general has concentrated on helping patients with Amyotrophic lateral sclerosis (ALS), a progressive motor neuron disease that has no cure and destroys a human's motor system. Birbaumer (2006b) created an SCP BCI specifically for patients who suffer from ALS to use. Patients were first trained to produce positive or negative SCPs that were based on an auditory cue or command. Once 70% control was achieved, patients then had letters and words appear on the screen from which to choose from to construct messages. The system is limited to about one bit per minute and requires a long period of training time to use successfully, often in the region of months (Birbaumer, 2006b). Both these factors are significant disadvantages of using an SCP BCI for healthy individuals. A method or technology will need to be found to improve the SCP BCIs bit per minute in order for it to be viable outside of a clinical setting.

An interesting aspect of SCPs is automaticity, a phenomenon that occurs in the late stages of skill acquisition (Logan, 1985). Logan (1988) found that cognitive skills became more automatic, more precise and interfere less with other tasks when practised. Neumann et al. (2004) aimed to discover whether the self-regulation of SCPs could be automated over time and thus be considered a skill. The research only used two participants, but showed preliminary evidence that SCP self-regulates over time. In a related study conducted by Hinterberger et al. (2005), they examined the neurophysiological changes in a participant who used SCPs to operate a BCI. Using fMRI, it was revealed that SCP shifts are closely related to an increase of the BOLD response in the brain of the participant. The data support the theory that human subjects learn to generate an SCP at will when learning to use an SCP BCI and can therefore be considered a skill.

However, patients with extended prefrontal lobe (Figure 2.2) lesions cannot learn SCP control (Lutzenberger et al., 1980). In a similar study, Strehl et al. (2006) have indicated that children can learn to control their SCPs. However, the assumption that participants with frontal deficits are not able to self-regulate brain activity related to attention could not be confirmed. Yet, in another related study Piccione et al. (2006) have demonstrated that the more advanced the disease state of a patient, the less useful an SCP BCI is for a patient to use. If SCPs cannot be generated by a section of the populace, this could be a major disadvantage for the SCP BCI. A conclusive study is needed to confirm or reject this result.

Another disadvantage of SCP BCIs when used for clinical populations is the reliance on eye movement and the available attention span of a participant. One or both of these factors are usually not available to locked-in or severely disabled patients, thus reducing the usefulness of an SCP BCI to this group. Employing the auditory modality and the use of stimulus presentations is a suggested possible alternative for these more severe cases of disabilities in order to utilise an SCP BCI, but this does not resolve the underlying problem (Birbaumer, 2006a).

SCP BCIs have been shown generally to have low bits per minute, long training requirements and a possible limited applicability to a section of the populace. These factors preclude the use of SCPs for this study.

2.8.2 Sensorimotor Rhythm BCIs

Alpha, beta and mu rhythms originate from the sensorimotor cortex (Figure 2.2) in the brain and can be detected by an EEG BCI (Bashashati et al., 2007; Jasper and Penfield, 1949). When a person physically moves a muscle, a particular rhythm is produced. A similar rhythm is produced when a participant imagines the same physical movement (Lang et al., 1996). Pfurtscheller and Lopes da Silva (1999) have indicated that voluntary movements resulted in a signal that ranges in the upper alpha and lower beta bands located close to the sensorimotor areas of the brain. A novel movement-imagery based BCI was developed for untrained participants using beta rhythm synchronisation. The BCI achieved classification accuracies of between 77% and 84% (Sasayama and Kobayashi, 2011). Pfurtscheller et al. (2003) have developed a system using beta rhythms and imagined movement to restore hand grasping to a tetraplegic patient. This resulted in enabling the participant to grip a cylinder with a robotic hand. These studies illustrate the ability of an EEG BCI to detect participant imagined motor movements and to have high detection success rates. It is reasonable to assume that it is more natural for a participant to imagine an action to move a robot in a direction. Thus a BCI that can detect a beta rhythm, such as the Emotiv, would be suitable for this study.

Furthermore, participants can be trained to control mu rhythms consciously and use the changes as a control signal to move a cursor on a video screen (McFarland et al., 1997). In a similar study, Wolpaw and McFarland (2004) have used mu rhythms to demonstrate multidimensional control of a cursor on a computer screen. The participants guided the cursor towards a goal that appeared randomly on the screen. The experiment revealed that the bits per minutes achieved fell into the range previously achieved with invasive BCIs implanted in monkeys. Mu rhythms fall in the same range as alpha rhythms, but are indicators of imagined movement. Like beta rhythms, the mu rhythms are detectable by the Emotiv, further enhancing its recommendation. The last rhythm type that will be discussed is alpha rhythms.

Klimesch's (1997) research has been focused around the question of how a search process finds the relevant information in memory. The results of several experiments have indicated that alpha frequency varies as a function related to memory performance. Furthermore, Klimesch et al. (2003) indicate that applying transcranial magnetic stimulation (TMS) can enhance task performance. TMS uses electromagnetic induction to prompt activity in specific or general parts of the brain, allowing the functioning of the brain to be studied. These results provided further evidence for the functional relevance of alpha rhythms in cognitive performance. Klimesch et al. (2003) further propose that monitoring processes serve to allocate resources to guide search and retrieval processes. Therefore, it was speculated that monitoring processes are related to the attention of a participant. A related study used memory to reveal that event-related changes measured using EEG indicated that peak alpha frequency (PAF) is positively correlated with long-term memory performance (Wolfgang, 1999).

Angelakis et al. (2004) have attempted to use PAF as a predicting variable for verbal cognitive trait abilities in young adults. The results of the study showed a correlation between reading vocabulary and response control after analysing reading and post-reading recordings. A related study by Hanslmayr et al. (2011) with alpha rhythms indicate that the brain does not process incoming stimuli mechanically, but rather that the current brain state modulates reaction to stimulus. Alpha activity has been shown to be a measurable factor related to a person’s memory and attention. There appears to be a relationship between alpha rhythms, memory and attention, but the relationship needs to be researched in more detail to understand better how memory works when using alpha activity as a measure. Once a better understanding is reached, the technology should be leveraged to solve real-world problems. For example, the technology could be a powerful diagnostic tool in education to detect students suffering from attention deficit disorder.

Alpha, mu and beta rhythms are all detectable by the Emotiv. The Emotiv will be shown to be usable as a research device for imagined movement and P300 Spellers in Section 2.8.3. Therefore, with the Emotiv, the participant simply has to imagine some imagery or a movement and the system is able to produce a control signal. Thus, the Emotiv provides a natural approach to control a robot for the participants.

2.8.3 P300 Evoked Potentials BCIs

Sutton et al. (1965) have conducted a study that used brief light flashes and clicks as stimuli for a BCI P300 device in order to determine if it was possible to detect whether a person felt certain or uncertain when a stimulus was presented. The results indicated that there was a difference between the waveforms generated by a person's brain when they are certain or uncertain about a stimulus presented to them. This research was the foundation of the P300 BCI.

This experiment was then further expanded by the oddball paradigm experiment. In the experiment, a participant is asked to distinguish between two stimuli, one common and one rare. The participant is then asked to perform a mental count of the stimuli. When the rare stimuli appear (defined as an unusual stimuli), a response is generated in the brain and measured by the BCI (Serby, Yom-Tov and Inbar, 2005). The oddball paradigm was first used by Squires et al. (1975) and is the basis of modern P300 BCIs such as the P300 Speller.

The next important step in the development of the P300 BCI was the P300 Speller developed by Donchin (1981). In a P300 Speller, a matrix consisting of letters taken from the alphabet (Figure 2.4) is displayed on the screen. The letters are then highlighted in quick succession. When the letter desired by the participant is highlighted, a P300 ERP is generated in the participant's brain. The letter is then selected by the computer and appended to the sentence (cf. Donchin et al., 2000; Farwell and Donchin, 1988; Sellers and Donchin, 2006).

One of the major advantages of a P300 Speller system is that little to no training is required by the subject to use the device (Birbaumer and Cohen, 2007). However, a P300 Speller is limited effectively to two outputs, a positive or negative response, which significantly restricts the usability of a P300 Speller for day-to-day tasks.

Figure 2.4: A stimulus matrix monitored by a subject (Donchin et al., 2000).

The P300 Speller continued to be developed and improved upon by researchers. Serby et al. (2005) attempted to develop a more sophisticated P300 speller by improving the information-processing speed and accuracy. This resulted in a similar information bit rate with an increase in accuracy. The study used six patients to keep the results comparable to Donchin's (1981) research. A related study conducted by Sellers and Donchin (2006) aimed to find out the effectiveness of a P300 BCI that used one of four elicited stimuli. In this case, the options *YES*, *NO*, *PASS* and *END* was presented randomly to the participants. Using two groups consisting of three ALS patients and the other using healthy participants, the results establish that the target stimuli could be discriminated from non-target stimuli with a fair degree of accuracy by both groups. In an associated study, Hoffmann et al. (2008) showed that high classification accuracies and bit rates could be obtained with five severely disabled and four healthy subjects. The participants achieved a classification accuracy of 100% and a bit rate per minute between 10 and 25 was achieved.

An interesting variant of the P300 Speller was the auditory P300 Speller. The device works by using directional cues of auditory stimuli that are presented to the participant through earphones. Using twenty participants, a mean accuracy of over 70% and 2.76 bits per minute was achieved (Käthner et al., 2012). Participants reported that the auditory speller had a higher cognitive workload than the visual speller. Despite this weakness, the results recommended the auditory speller as a viable alternative. These studies indicated that the P300 BCI was an accurate device and was usable by disabled participants as well as healthy individuals. However, the limited outputs have yet to be addressed. It is possible, when considering how a P300 Speller functions, that this BCI will never be capable of more than positive or negative responses. With this limitation in mind, a possible way to improve the bits per minute of the BCI was by improving the interface.

Towards this end, a virtual smart house was developed by Postelnicu et al. (2012). A P300 BCI was used to control a main menu with a number of individual masks that led to a supplementary menu of commands to control different items inside the house. The interface, however, was effectively remote-control driven and thus not suitable for communication. A more suitable approach was the proposed dictionary-driven P300 speller by Ahi et al. (2011). The study was conducted with 14 participants who spelled 15 four-letter words. Using the custom dictionary, the mean accuracy increased from 72% to 95%, which is a large improvement. These studies worked towards improving the interface of a P300 Speller, but more research is required. In general, P300 Speller screens are laid out using an A–Z and 0–9 format. It could be that a QWERTY keyboard would be more efficient or some design decisions from mobile devices could be used. A mobile phone requires an alphanumerical keyboard that takes up a small amount of space and these techniques could be applied to the problem.

The P300 Speller is a promising device with potential to not only be used for persons with disabilities, but for healthy individuals as an additional or alternative communication channel. However, this study required a BCI that could be used in the most natural way possible and it was for this reason that a P300 BCI was not used for this research. The next section details the SSVEP BCI, a type of BCI that works in a similar way to a P300 Speller BCI.

2.8.4 Steady-State Visual Evoked Potentials (SSVEP) BCIs

A SSVEP is the natural brain response elicited when the retina is excited by visual stimuli, typically, flickering LED lights. When a SSVEP is generated, the signal could be detected and used to call a command.

In a landmark study, Morgan et al. (1996) indicated that SSVEP reflects an enhancement of neural responses to stimuli that occur where the participant's attention was directed. A related study by Müller et al. (1998) recorded SSVEPs from the scalp of subjects whose attention was concentrated on a flickering light-emitting diode (LED) in one visual field, while ignoring a similar display flickering at a different frequency.

The two approaches available to SSVEPs using LED lights for a BCI are to mount LED lights on the device itself or display the commands on a flickering screen near the device. The first approach was used by Muller-Putz and Pfurtscheller (2008) to try and restore the grasp function to spinal-cord injured individuals. Four healthy participants used SSVEPs to control electrical hand prostheses, with accuracy results between 44% and 88%. The study indicated that when operating asynchronously it is feasible to control a neuroprosthetic device with the flickering lights mounted on its surface. These results are further supported by Ortner et al. (2010), who used an asynchronous SSVEP BCI with seven individuals to move an orthosis, a device used to improve an individual's movement function. Without training, the subjects achieved reasonable control with accuracies at approximately 78%. However, there was a high false positive rate and the subjects reported disliking the flickering lights. These results highlighted the major disadvantage of a SSVEP BCI, namely the requirement for flickering visuals, which can distract participants.

The second approach was to put the commands on a flickering screen such as the robot FRIEND II (Figure 2.5), which used SSVEP to send high-level commands to the rehabilitation robotic system (Valbuena et al., 2007). The system offered a manipulator

Figure 2.5: FRIEND II system (Valbuena et al., 2007).

mounted on an electrical wheelchair, which was controlled via a menu presented on a screen. The study revealed that a task could be executed in as little as five consecutive commands. A similar study by Mandel et al. (2009) used a BCI that interpreted SSVEPs to steer a robotic wheelchair. The results of the study showed that eight of the nine untrained subjects could successfully navigate an automated wheelchair with as little as ten minutes of preparation.

Similarly, Zhang et al. (2012) developed a platform to control a mobile robot remotely through the internet using SSVEP. A smart phone transfers the command from the server to the robot and transmits a video stream as feedback to the user. These studies all indicate that an SSVEP BCI can be used successfully to control a robotic apparatus and has been considered for use with this study.

SSVEP BCIs have the advantage of not requiring specific training by the user. Beverina et al. (2003) and Allison et al. (2010) have identified who could use an SSVEP BCI. The results showed that most people could use the SSVEP BCI system in a very noisy setting and that performance tended to be better in both young and female subjects. Comparatively the SSVEP BCI relies on eye movement to function, which was a distinct disadvantage. Towards addressing this problem, Kelly et al. (2005) presented strong evidence suggesting that the SSVEP can be used as an electrophysiological correlate of visual spatial attention that can be used on its own or in conjunction with another BCI technique to achieve control. Thus SSVEP could be a strong candidate for use within a NUI.

The SSVEP BCI could have been used for this study, had the study not required a natural approach. Thus, the use of imagined movement in the form of beta rhythms was more appropriate. This study intends to use an EEG BCI; the candidates available are discussed in the following section.

2.9 Candidate EEG BCI Systems

A number of EEG systems were considered for use with this study. These ranged from a complete solution, including the EEG hardware and software needed, to only a software suite that could be used by a researcher with his/her own custom-made EEG equipment. The three systems that were considered for use are discussed below.

2.9.1 Cyberlink

The Cyberlink (Figure 2.6) consists of three components: a headband, an interface box, and a software application that was supplied with the device. The headband contains three sensors that are placed on the user's forehead to detect and amplify neurophysiological rhythms. Three command signals are derived from the headband; eye movements, brain activity and facial-muscle activity (Mateo and Feufel, 2000).

Figure 2.6: An early version of the Cyberlink system (Doherty et al., 2000).

The Cyberlink interface was popular as a research tool around the turn of the millennium. Doherty, Stephenson and Engel (2000) conducted research using the Cyberlink and a series of custom-written Yes/No programs on severely brain-injured patients. The goal was to see if the device could be used for recreation to relax a patient with activities such as completing puzzles and mazes. The study ascertained that the Cyberlink system could successfully be used for recreation and communication (Doherty et al. 2000). An associated study by Doherty et al. (2001) used the Cyberlink with cerebral palsy patients to measure how relaxed patients became when they used a variant of the Yes/No program to control a robot to perform basic tasks. The results showed that the device was useful for communication but whether or not it relaxed the patient was inconclusive. The Cyberlink was an older device that was limited by the technology of the time and the limited sensors available for the researcher. The Cyberlink was important, because it was one of the first commercial products made available for the public. However, newer and better devices are now available, making the Cyberlink a poor choice for this study.

The following section discusses the research related to the BCI2000 software.

2.9.2 BCI2000

BCI2000 (Figure 2.7) is an open-source software project and was originally created to help BCI researchers develop software systems for their research. Although the software comes with no hardware component, it has been modified to be usable on a large number of existing hardware systems. As defined on the organisations' website:

> *BCI2000 is a general-purpose system for brain-computer interface (BCI) research. It can also be used for data acquisition, stimulus presentation, and brain monitoring applications* (BCI2000, n.d.).

Figure 2.7: Image of a system utilising the BCI2000 software (BCI2000, nd).

The BCI2000 was utilised in a BCI system designed by Wolpaw (2007) for people with disabilities to use in their homes. During the study's preliminary stages, the system showed potential to enhance the quality of life of a person with disabilities. The system can, however, only be used for basic communication and control functions. Lotte et al. (2009) utilised the BCI2000 and demonstrated that EEG BCIs could be used successfully by users in motion with as little as three electrodes attached to their scalps, as an example for using BCI in day-to-day activities. These studies demonstrated the versatility of the BCI2000 platform, as any EEG BCI could be fitted to work with the system and give the researcher a full set of low cost tools to work with.

The BCI2000 was considered for use with this study, but at the time (2010), support for Microsoft products or the Emotiv had not been added. As of 2012, this functionality has been added. The next section will discuss the Emotiv headset in detail.

2.9.3 Emotiv EPOC

The Emotiv (Figure 2.8) is a commercial device developed for use by the general public, developers and researchers interested in BCIs. The product is being marketed towards multimedia users as an extra *sense* in their multimedia applications. According to the Emotiv commercial website:

> *Based on the latest developments in neuro-technology, Emotiv has developed a revolutionary new personal interface for human computer interaction. The Emotiv EPOC is a high resolution, neuro-signal acquisition and processing wireless neuro-headset* (Emotiv, n.d.).

Figure 2.8: Emotiv EPOC being used in a research study (Anderson et al., 2011)

A number of recent (2010) research studies are presented to show the validity and motivate the use of the Emotiv as a research tool. Postgraduate students from Dartmouth College in the United States conducted an experiment that used the Emotiv to control a contact list application on an iPhone (a type of smartphone). The Emotiv was configured as a P300 Speller and detected when a user concentrated on a contact they wished to select. The system then dialled the corresponding phone number. The results produced were promising overall but required the use of data averaging over a large number of trials to get a response from the system. This response delay resulted in frustration for the user due to a feeling of *unresponsiveness* from the system (Campbell et al., 2010).

In a similar study, the Emotiv was used to test P300 detection techniques for research purposes. The results indicated that the Emotiv could detect P300 events effectively enough for researchers and was valid as a research tool (Rosas-Cholula et al., 2010). In a related study, the potential of the Emotiv as portable EEG for use with a smartphone was tested. The developed system was capable of stimulus delivery, data acquisition, logging, brain state decoding and 3D activity visualisation. The system was then used to analyse the P300 Event Related Potentials when viewing affective images (images that elicit an emotional response). The results exhibited differences between affective and neutral images as well as pleasant and unpleasant content (Petersen et al., 2011). These studies demonstrate that the Emotiv is suitable for research using P300 Evoked Potentials. Although the P300 approach will not be used for this study, the fact that an Emotiv was capable of this demonstrates the versatility of the headset.

In an unrelated study, the Emotiv was used to measure the cognitive load placed on participants when using different types of graphical data representations. Cognitive load in the experiment was measured by analysing the spectral, temporal and spatial patterns of brain activity (Anderson et al., 2011). A recent study by Vourvopoulos and Liarokapis (2012) used the Emotiv and 54 participants to measure the responsiveness of the Emotiv to navigate a robot using imagined movement. The response was found to be overwhelmingly positive. However, the results were qualitative in nature, which although informative, does not have the value a quantitative based study would.

The Emotiv has a disadvantage compared to dedicated research BCIs. The headset has less than a quarter of the channels used in most studies with only 14 sensors (Newman and Norman, 2010; Parra et al., 2005). This means the data sample rate is nearly one tenth of more powerful setups. Although the sensor count is low, studies have shown that a BCI can be used with as little as three sensors (Lotte et al., 2009).

The studies discussed illustrate that although the Emotiv is a relatively new device it has been used successfully in a range of studies that supports the decision to use the headset with this study. The next section discusses the available literature on the working principles of the Emotiv.

2.9.3.1 Emotiv Working Principles

The Emotiv system measures the electrical activity associated with the brain and facial muscles. The Emotiv BCI then takes these signals and converts them into machine-understandable control signals (Figure 2.9). The Emotiv is a non-invasive BCI and uses two common artificial and neural learning techniques.

These are namely the McCulloch-Pitts Model (MCP) and the Back Propagation algorithm. The McCulloch-Pitts Model is the simplest kind of neural modelling currently available and was created as a workable model to understand how the brain could create highly complex patterns by using many basic cells that are connected together. A group of MCP neurons grouped together is known as an artificial neuron network. McCulloch and Pitts showed how to encode any logical proposition by an appropriate network of MCP neurons. The theory was that anything that could be done with a computer could also be done with a network of MCP neurons. The McCulloch-Pitts Model as it was implemented in the Emotiv was classified as supervised learning (McCulloch and Pitts, 1943).

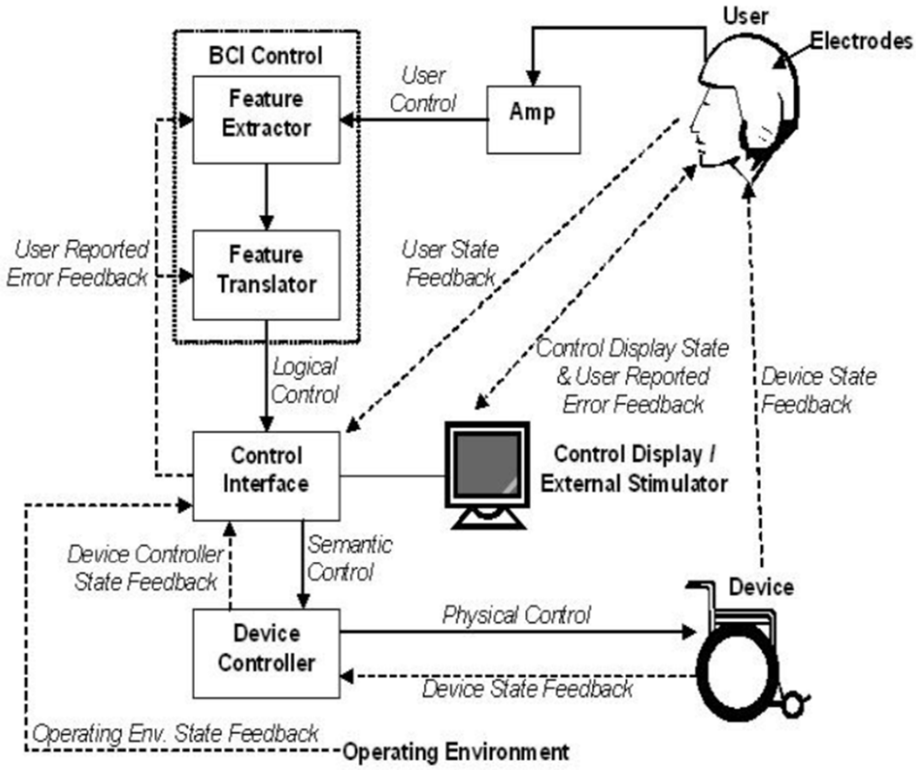


Figure 2.9: Block diagram of a typical BCI (Neural Sensing, nd).

The Back Propagation algorithm used by the Emotiv is a supervised learning method and is a generalisation of the Delta rule (Hirose, Yamashita and Hijiya, 1991; Horikawa, Furuhashi and Uchikawa, 1992; Van Ooyen and Nienhuis, 1992). The Delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. With a given input, the output of the algorithm is compared to the expected result. If there is zero difference between the output and the expected result, no learning has taken place. If there is a difference, the weight used in the algorithm is adjusted to reduce the difference. For a given input vector, the output vector is compared to the correct answer. The Back Propagation algorithm relies on two phases, namely the propagation phase and the weight update phase using the delta rule. The two phases produce a ratio that influences the speed and quality of learning, which is known as the learning rate. The learning rate was used by the Emotiv to produce a representation of the effectiveness of a training session (in percentage). The two phases of the algorithm are repeated until the researcher is satisfied with the results of the learning rate.

Although the Emotiv was chosen as the BCI for this study, the following section will briefly touch on custom BCI systems to round off the discussion.

2.9.4 General BCI Systems

This section discusses BCI systems that have been custom built to meet a researcher's needs. Often these systems are expensive and are only used by the laboratory in question for specific research.

- Researchers created a prototype BCI that was shaped like a headband for ease of use. The BCI-headband used four disposable dry electrodes, which had real-time processing implemented on a smartphone to be used with a driving simulator to measure how alert a participant was. Recordings of the driving simulator showed that a driver can be kept at optimal performance by reading a driver's alertness with the BCI-headband (Lin et al., 2008; Lin et al., 2009).
- A novel system was developed by Tangermann et al. (2009) that linked a pinball machine and a BCI to demonstrate that fast and well-timed control is possible with a BCI that picks up motor imagery. The study used four participants and they reported enjoying the experience and having control over the machine which is supported by the results.
- An unrelated study was completed on how a P300-evoked potential BCI system could be used to enhance a social network website such as MySpace or Facebook. The study revealed that people can annotate the multimedia content by means of their brainwaves and a custom P300 Speller system (Yazdani, Lee and Ebrahimi, 2009).
- Finally, a military application called Warship Commander Task (WCT) supplied a simulated navy command and control environment for the United States' military. The system handled real-time analyses of EEG recorded from a BCI to monitor indexes of alertness, cognition, and memory, which was given as feedback to an operator, observer or machine, depending on the requirements. The WCT required

that the user monitors groups of incoming aircraft and then to warn them about and destroy hostile tracks. The results indicated that the device was predictive of fatigue-related decrements in accuracy and reaction time that occurred hours before the actual onset of sleep (Berka et al., 2004).

This completes the section on EEG BCIs. The following section discusses studies that used robotics and BCIs, which provide motivation for this study's methodology and design.

2.10 BCI Robotic Studies

The ability to give movement back to a person who has lost a limb is one of the main goals for research in the BCI field (Wolpaw, 2007). In order to achieve this it was logical that researchers would need to link BCIs to advanced robotics. Barbosa et al. (2010) created a BCI that controlled a 5.4 kg mobile robot by correlating four imaginary movements to four directions. Feet, tongue, left arm and right arm movement correlated with the four robot movements *stop, move forward, turn left* and *turn right*. These correlated movements are not intuitive. In a similar study, Li et al. (2012) used a BCI to create a platform that could identify the imagined movements *turning right, turning left* and *walking forward*. The commands were used to have the corresponding action occur on two different humanoid robot types, the KT-X PC (Figure 2.10 (a)) and the NAO H25 (Figure 2.10(b)).

Minati et al. (2012) conducted a proof-of-concept study using a vision-guided robot arm and an fMRI based BCI. The study had five participants that used left and right imagery with speech recognition to move a robotic arm (Figure 2.10 (c)). The participants randomly placed coloured pawns into a cup achieving control of about 1.5 bits per minute.

BCIs have been shown to enable persons with disabilities and serve as an extra communication channel for healthy individuals. However, it was previously established that BCI EEG's have a low bit per minute and are therefore not ideal for complicated tasks such as the low level manoeuvring of a robotic arm (Grigorescu et al., 2012). The challenge for researchers is to find an alternative means of utilising a BCI to complete complex tasks.

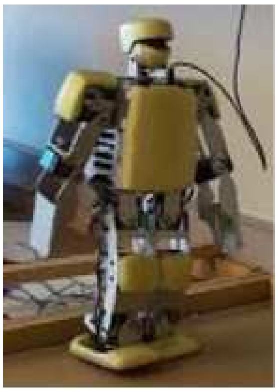
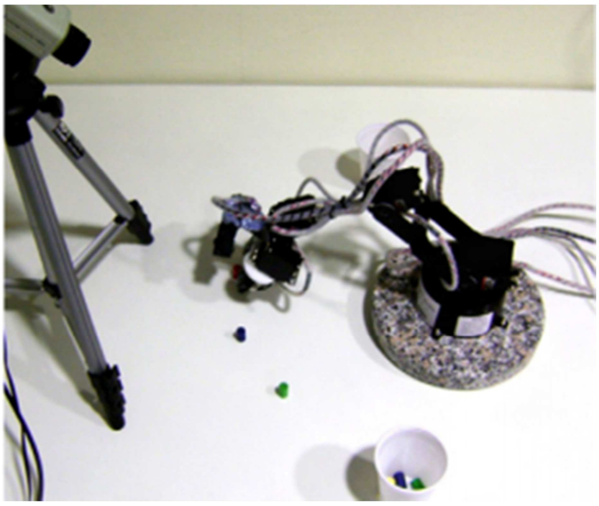


Figure 2.10 (a): KT-X PC robot (Li et al., 2012).

(b) NAO H25 robot (Li et al., 2012).



(c) Robotic arm picking up coloured pawns (Minati et al., 2012).

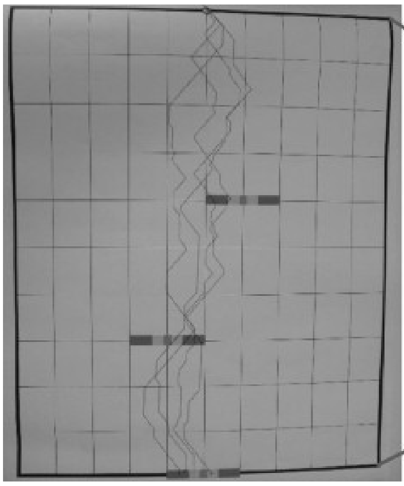
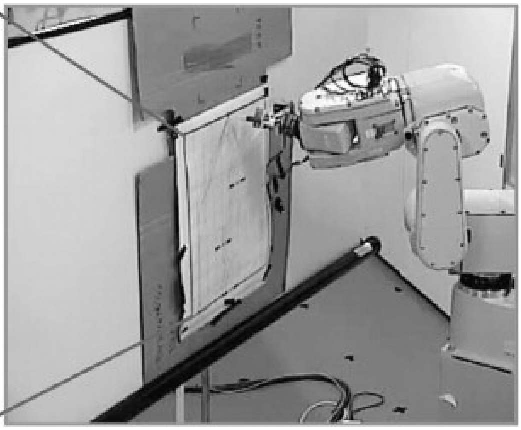


Figure 2.11 (a): Paper with path and goals (Iáñez et al., 2010)



(b) Robot arm drawing path (Iáñez et al., 2010)

For example, advances in robotic technology can be leveraged with an EEG BCI to control a partially autonomous robot in order to perform complex tasks (Bell et al., 2008). The system used a dynamic image-based P300 BCI to select between alternative commands such as walking or picking up an object and achieved an information rate of 24 bits per minute. Similarly, a P300 BCI was used to move a wheelchair from one room to another in a building using a context-sensitive interface (Rebsamen et al., 2007).

BCIs have also been used successfully to move a robot arm by detected imagined movement along a path with goals represented by bars (Figure 2.11(a)). The robot arm is kept constant and moved along the YZ plane, as the participant attempts to hit the goals, while drawing a path down the page (Figure 2.11(b)). The aspect that these studies have in common was the attempt by the researchers to abstract the commands away from low-level tasks to improve the bit rate of the devices. For example, instead of having the BCI control the actuators on a robotic arm, simply have a command like *move left,* which contains all the commands necessary to make a robot arm move towards the left. Although the abstraction of commands was a solution, it does not solve the underlying problem of the low bit rate of the BCI system. Additionally, it can be argued that by abstracting the commands for the participant, finite control of the device is lost. For example, a user could not give a handshake unless the action had been programmed into a command previously.

These studies are only representative of the existing research between BCIs and robotics, but illustrate the strong relationship between the technologies.

2.11 Summary

This chapter summarised representative literature for this research with particular emphasis on the usability of EEG BCIs when used for navigation. Usability was defined as the capability of the system to be learnable, efficient, effective and satisfying to the user when used under specified conditions. The different types of BCIs were discussed and the choice to use an EEG BCI was motivated. Specifically a commercial EEG BCI called the Emotiv was utilised to navigate a pair of small robots.

A natural approach for a command signal with the Emotiv was needed for the participants of this study. Subsequently sensorimotor rhythms were chosen as the technique that can utilise any imagery generated by a participant. The robots navigated were a pair of Mindstorm NXT robots and a standard US layout keyboard was chosen to represent the traditional input method.

The following chapter will discuss the research design and methodology in detail.

Chapter 3: Research Design and Methodology

3.1 Introduction

The preceding chapter was a summary of a selection of the available literature related to this study. This chapter discusses and motivates the research design, the relevant methodologies available for the chosen research design will be discussed, and the methods that were chosen will be motivated. Usability testing will be discussed in detail, followed by a section on how the data captured for this study will be analysed.

3.2 Research Design

Research as a general concept is the process that involves obtaining knowledge by using a selection of objective methods and procedures. The term *objective* refers to methods that do not rely on opinions but rather rely on sound scientific methodology. The research design is the logic behind the chosen research methods and techniques and serves as a blueprint for the study (Welman, 2006).

The framework provided by Welman (2006) served as the main structure used to determine the research design. However, the approach proposed by Welman (2006) strictly categorises research as quantitative or qualitative. The approach used for this study, however, intended to have both quantitative and qualitative components. Thus the Welman (2006) approach was extended to include the work of Creswell and Clark (2011).

For this stage, Rugg and Petre (2006) suggest using a methodology that is based on the expected outcomes of the study. Recall that the main aim is to investigate the usability of a BCI for robot navigation. Thus, the outcomes of this study will require measures of usability, which can be quantitative or qualitative in nature.

The second step was to determine the research topic and research problem (Welman, 2006). When considering the research problem an important factor that needs to be considered is the research field that the study will take place in. This research falls under the purview of Human-Computer Interaction (HCI) which, as previously mentioned, is the promotion of the interaction between humans and computers including the tools used during the interaction (Giacoppo, 2001), the tool in this case being the BCI itself. It is important to note that HCI research is different to general scientific research as it is heavily influenced by the principles and controls of the scientific method, as well as many non-scientific methods such as psychology (Giacoppo, 2001; Mason and Birch, 2003). As the proposed study was based on HCI, this influenced the design of the study. The study investigated alternative interfaces to the keyboard and thus the study falls under the purview of NUI (Section 2.3). For this topic a set of hypotheses was created from the research problem (Section 1.5) which is repeated here for convenience:

- $H_{0,1}$: Exposure to a traditional input method does not influence a user's performance when manoeuvring a robot using a BCI.
- $H_{0,2}$: There is no difference in a user's performance when using a traditional input method compared to using a BCI when manoeuvring a robot.
- $H_{0,3}$: Repetitive use of a BCI has no effect on user performance when using a BCI.

The third step is an in-depth literature review to achieve a current state of knowledge for the researcher (Welman, 2006). This step was evidenced in Chapter 2.

The final step is the research design itself. This requires the researcher to determine if the research is quantitative, qualitative, or a mixed-methods research design. Mixed methods research is defined as "*those that include at least one quantitative method and one qualitative method, where neither type of method is inherently linked to any particular inquiry paradigm*" (Creswell and Plano Clark, 2011, p. 2). This research used both quantitative and qualitative data and was, therefore, a mixed methods research design.

The following section will discuss the research methodology applicable for this research design.

3.3 Research Methodology

The discussion for this section will start with sampling methods applicable for the research design followed by data collection. The applicable evaluation methods are discussed and the methods used will be motivated. The relevant usability testing is discussed and the section concludes with a discussion on how the captured data were analysed.

3.3.1 Sampling

Sampling can be broken down into two broad categories, namely probability samples and non-probability samples (Berenson and Levine, 1979). Probability samples are obtained from a sampling method that uses randomised selection (Rugg and Petre, 2006). By definition, a random sample is one selected from a population in such a way that every subject has an equal chance of selection. A random sample is ideal for use in accurate statistical analysis (Mendenhall and Sincich, 2003). The four most common types of probability samples are simple random samples, systematic samples, stratified samples and cluster samples (Berenson and Levine, 1979).

In a simple random sample, every subject has the same probability of being selected. Systematic sampling takes place when each member of a population is given a unique number. Using the sample size, the interval size is determined as the population size divided by the sample size. A random integer is generated within the range of the interval size. From this, a member is selected. A stratified sample requires breaking the sample into homogeneous strata and then selecting a random sample from each stratum. Cluster samples are obtained by dividing a population into clusters and then randomly sampling the clusters (Preece, Benyon and Davies, 1993; Welman, 2006). A specific type of participant was needed for each group; therefore, using a probability sample technique was not suitable.

Non-probability samples might be easier to obtain but have the disadvantage that the sample cannot indicate how representative it is of the population as a whole (Berenson and Levine, 1979). The six kinds of non-probability sampling techniques are convenience sampling, quota sampling, purposive sampling, snowball sampling and self-selection sampling. Convenience sampling takes place when the most convenient sample is chosen that is near and readily available to the study. Quota sampling has the sample selected according to a particular unit of analysis, while with purposive sampling the sample is restricted to a predefined sample based on a researcher’s experience. Snowball sampling takes place when a few individuals representative of the sample are approached and asked to identify other representative individuals for inclusion in the sample. Self-selection sampling occurs when a person is selected from a sample based on their desire to participate in a study (Welman, 2006). A mix between a convenience sample and self-selection was employed to recruit participants.

The participants were sampled from two different areas. The first sample was a convenience sample sourced from students taken from the University of the Free State's Qwaqwa Campus. The second sample was a convenience sample sourced from students from the University of the Free State Bloemfontein Campus. Each sample set was made up of an equal number of males and females to make up a total group of twenty students per group. A self-selection method of sampling was employed to recruit participants. It was thought that these volunteer participants would be motivated and more likely to complete all seven required sessions.

The actual recruitment method used is discussed in the next section.

3.3.1.1 Recruiting Participants

Important limitations when recruiting participants are the economic and scientific limitations that are applicable to the study. A study must be suitable for the resources available to a researcher. However, the number of participants used should be based on experimental evidence and allow for a complete evaluation.

Bastien (2010) has determined that 4–5 users are sufficient to find above 85% of the usability problems in an interface. Spool and Schroeder (2001), however, have shown that using five users only detected 35% of the usability problems in a web interface. Nielsen (1994) recommends twenty participants or more when conducting quantitative user testing. Therefore, there are no clear guidelines on how many participants are required for an usability test (Bastien, 2010). As a conservative choice Nielsen's (1994) guidelines will be used and each group will comprise twenty participants.

Normally it is also required that participants are classified according to their expertise with the system (Faulkner, 1998). However, for BCIs there are relatively few experts, since most BCI systems are especially designed for users who are severely disabled (Wolpaw and Wolpaw, 2012). Thus, novice participants were recruited for this study, which is ideal for determining the applicability of the BCI as a NUI.

With sampling and recruitment being discussed, the next step is to discuss how the data were collected from the sample.

3.3.2 Data Collection

Empirical research requires direct or indirect observation or experience in order to gain knowledge (Olivier, 2004). Empirical studies can only be performed by using primary or pre-existing data that have been analysed in a novel way. It was, therefore, necessary to collect primary data (new data) or use pre-existing data which needed to be analysed in a unique way (Lapan and Quartaroli, 2009; Mouton, 2001). Since this study had no easily accessible pre-existing data, new data had to be collected.

According to Mouton's (2001) classification, the correct data collection methods to use for an empirical study are surveys and experiments. This compares favourably with the recommended design from Preece et al. (1993) and Olivier (2004). This study will utilise an experiment, which can be conducted either in the field or in a laboratory under controlled conditions. Experiments that are comparative studies investigate the differences as well as the similarities between units of analysis (Preece et al., 1993). As this study compares two groups in an experimental setting, it will be a comparative experiment with surveys being used to gather subjective data.

The evaluation methods applicable to this kind of research and the methods used will be highlighted.

3.3.3 Evaluation Methods

This section will discuss some of the evaluation methods available for a mixed-methods study, namely surveys, expert reviews, direct observation, model-based evaluation and experiments.

3.3.3.1 Surveys

Surveys are usually used in studies that are qualitative in nature and aim to provide a broad overview of a representative sample of a population (Berenson and Levine, 1979; Mouton, 2001). The two most common kinds of survey techniques are questionnaires and interviews.

3.3.3.2 Questionnaires

A questionnaire is a form that contains questions that need to be answered by participants in a study. Usually these questions are used to collect demographic information, views and interests of participants (Sharp, Rogers and Preece, 2007).

In terms of HCI, questionnaires are often used to obtain reactions from a user on an application or website (Kuter and Yilmaz, 2001)., Questionnaires are specifically used when the researcher is looking for subjective data and are considered to be a fairly reliable means of obtaining large amounts of data, if constructed correctly (Sharp, Rogers and Preece, 2007). It can be administered by an interviewer, or be self-administered by the participant. Questionnaires are often given in an online form via e-mail, computer-direct and web-based questionnaires (Kuter and Yilmaz, 2001).

A questionnaire can be formatted in an unstructured, structured or combination of structured and unstructured way (Sharp, Rogers and Preece, 2007). Unstructured questions are also known as open questions. These types of questions encourage respondents to elaborate on their answers but often these answers are difficult for a researcher to analyse. Structured questions, also known as closed questions, force a participant to select an answer from a set of predetermined answers and are far easier to analyse (Sharp, Rogers and Preece, 2007).

The current study used two questionnaires: a structured, self-administered recruitment questionnaire given at the beginning of the study and a structured, self-administered, computer-directed questionnaire administered at the end of the study. The recruitment questionnaire included a section that measured a participant's expertise with a traditional input method, where expertise is a measure of frequency and length of use (Rosson, 1984). Additionally, the CAS from Marcoulides (1989) was included in the recruitment questionnaire to help classify the participants into groups based on their exposure to traditional input methods.

3.3.3.3 Interviews

An interview is a conversation between two people where questions are asked by the interviewer to obtain information from the interviewee. An interview can be administered personally or via audio communication (Preece et al., 1993; Welman, 2006).

Interviews can be structured, unstructured or semi-structured. A structured interview has the interviewer ask questions from a compiled questionnaire known as an interview schedule. Unstructured interviews are informal and used to explore a general area of interest. Semi-structured interviews are a mixture between structured and unstructured and fall between the two types (Preece et al., 1993; Welman, 2006).

An interview was not used in this study.

3.3.3.4 Expert Reviews

For an expert review, a usability expert is asked to inspect and review a system. Guided by heuristics, experts will often step through tasks, roleplaying typical users of the system trying to identify problems. Expert reviews usually include heuristic evaluation, guideline reviews, pluralistic usability walkthrough, consistency inspection or a cognitive walkthrough. The reviews are efficient, relatively quick compared to a laboratory approach and can provide prescriptive feedback. A disadvantage of the approach, however, is that a user is not actively involved in the process (Sharp, Rogers and Preece, 2007).

Expert reviews were not used.

3.3.3.5 Direct Observation

Direct observation takes place when an observer directly observes participants and serves as the measuring instrument for the study (Welman, 2006). The observation can be conducted in a specially chosen location such as a usability laboratory or an informal setting such as the user's residence (Preece et al., 1993). Sometimes mechanical aids such as audio or video recordings are used, which are then evaluated after the fact. The results can be recorded and analysed qualitatively or quantitatively (Welman, 2006).

The data analysis that takes place after the observations are completed is either task-based or performance-based. Task-based analysis measures how participants have approached the given task and performance-based analysis measures performance from the collected data (Preece et al., 1993). However, the disadvantages are that in most cases the reliability and validity of the captured measurements are reliant on the skill of the observer and the data analysis is time consuming (Preece et al., 1993; Welman, 2006).

Direct observation was utilised by the facilitator to record completion times of a task and the errors made by a participant.

3.3.3.6 Model-based Evaluation

Model-based evaluation takes place when a model is created to predict user behaviour. A model is a psychologically valid way of depicting persons who are the users of the system (Smith-Atakan, 2006). Model-based evaluation can cost less than user testing, but the model must first be tested for validity, which is a time-consuming process.

Model-based evaluation was not used in this study.

3.3.3.7 Experiments

An experiment is the collection of data about a population that is controlled by an experimenter. The data can be captured in the form of measurements and observations. The aim of an experiment is to answer a question or to test a hypothesis (Sharp, Rogers and Preece, 2007). The standard procedure for experiments compares two or more cases with each other to measure a variable the experimenter is interested in (Olivier, 2004).

A variable is defined as anything that is categorical and capable of having more than one value. Variables can be either dependent or independent (Mendenhall and Sincich, 2003). Dependent variable values are reliant upon other variable(s). An independent variable is unaffected by other variables. Experimental research involves isolating an individual independent variable that may influence a dependent variable (Cohen, Holliday and Holliday, 1996). The independent variable is then manipulated to ascertain whether there is an effect on the dependent variable and by what magnitude (Cohen, Holliday and Holliday, 1996). Experiments are designed to be quantitative studies and are robust research methods. They allow for the isolation of independent variables, which could cause variance in dependent variables (Mouton, 2001).

HCI experimentation can be a form of a comparative experiment. A comparative experiment takes place when a system is tested against an existing system or different design. The system can also be tested in isolation. A cause and effect relationship must be established in an experiment. Experiments are used to compare alternate designs to measure the effect of a certain variable between the designs (Faulkner, 1998). This study compared two groups of participants to each other; therefore, the experiment followed a comparative experiment study design.

3.3.4 Usability Testing

Usability testing (or user testing) is a process that uses people as testing participants who represent the targeted population to evaluate the degree to which a system meets the specific usability criteria (Rubin and Chisnell, 2008). A typical user's performance is measured by having a participant perform representative pre-designed tasks expected from the system (Sharp, Rogers and Preece, 2007). Usability testing is a research tool whose methodology is based on classical experimental methodology. Although many metrics are used to measure users' performance, it is commonly measured in terms of number of errors made and the time taken to complete a task (Rubin and Chisnell, 2008; Sharp, Rogers and Preece, 2007).

Usability testing is a form of empirical testing that involves conducting a usability test with the intended users of the system, followed by an analysis of the user interaction via predefined usability measures. It is also possible to gather subjective data from users about the system by having users complete a test or questionnaire (Sharp, Rogers and Preece, 2007). The subjective data can then be analysed resulting in subjective measures of effectiveness, efficiency and satisfaction (Macaulay, 1995). This data can ultimately be used to ascertain whether or not the system meets the needs of the user (Macaulay, 1995; Sharp, Rogers and Preece, 2007).

As well as subjective data, Buscher and Biedert (2010) have shown that BCIs can successfully record qualitative and quantitative data that are necessary for evaluation. This research will utilise usability testing, and the Emotiv will be used for the quantitative aspect using a custom program (Section 4.6), while the qualitative aspect will be captured via a recruitment and a post-test questionnaire (Section 3.3.3.1.1).

The next section will detail how to conduct a usability test.

3.3.4.1 Conducting Usability Testing

In general, conducting a usability test involves participants being observed while completing a task, using a system of interest to an evaluator (Cox and Walker, 1992). According to Bastien (2010), there are a number of general steps to be followed when conducting a usability test:

- Define the test objectives;
- Recruit test participants;

- Selection of test participants;
- The creation and description of user tasks;
- Define how data will be measured and recorded;
- Setup of test materials and the test environment;
- Choose tester and setup test protocol;
- Design and/or selection of questionnaires and data analyses methods;
- Communication and presentation of test results.

These steps were followed when designing the usability test.

Most usability tests are conducted with one participant at a time, although using two participants simultaneously is possible, using a method called paired-user testing. Remote usability evaluation is also possible where the evaluator and the participant are not in the same room when the usability test is performed. This method can be performed synchronous or asynchronously. In a synchronous approach the evaluator collects the data and manages the evaluation session in real time while an asynchronous approach has no facilitator and is not performed in real time (Bastien, 2010). For this study, the facilitator was in the same room as the participant, and data were collected synchronously with one participant at a time.

A usability test comprised of a number of user tasks, the design of which is discussed next.

3.3.4.2 Designing User Tasks

A user task is what the user wants to achieve with the system and can be defined as a series of activities and actions that are considered necessary to achieve the user's goal. An action is a very simple task that requires no problem solving (Sharp, Rogers and Preece, 2007).

Task analysis is hierarchical in nature, meaning that all tasks can be broken down into subtasks based on individual actions. Tasks used in user testing are considered benchmark tasks. This means the tasks are considered standard tasks that can be performed using the system (Sharp, Rogers and Preece, 2007). Important tasks should feature early in the usability test as it is likely that not all the participants will finish all the tasks (Beelders, 2006).

The tasks were organised into levels on a curve of perceived difficulty. The further a participant progressed along the curve the more actions they were required to manage, which increased the cognitive load of the participant and thus the difficulty of the task.

Usability testing was conducted inside the structure of an experiment for this study. This process is discussed in the next section.

3.3.4.3 Conducting experiments in usability testing

User testing as experiments is a means to compare alternative designs of a system to establish which design is the better choice (Preece et al., 1993). As mentioned previously, it is important that when conducting experiments in usability testing, also known as experimental evaluation, that the evaluator can manipulate a number of factors related to the usability of the system. The evaluator then studies the effect of the factors on the user performance (Preece et al., 1993).

An experiment should be conducted in a controlled environment where the variables of interest can be monitored. By using a controlled environment, limiting independent variables and carefully measuring the dependent variables it is possible to use statistical analysis to test the validity of a stated hypothesis (Mendenhall and Sincich, 2003; Olivier, 2004; Smith-Atakan, 2006).

The experiment methodology was applied when measuring the usability of the Emotiv in this study. The independent variables used were the groups of participants and the input methods, the keyboard and the Emotiv. The dependent variable was the usability metrics, namely time taken and errors made.

An important aspect before analysing data is determining the correct metrics to use for the study. This aspect will be discussed in detail within Chapter 4.

The next section briefly discusses how the data will be analysed.

3.3.5 Data Analysis

The final step in usability testing is to analyse the data collected from the experiment as both experimental and survey methods require statistical analysis of the collected data (Olivier, 2004).

Statistics can be descriptive or inferential (Olivier, 2004; Welman, 2006). Descriptive statistics are values that can be calculated from a population or sample that describe the group (Olivier, 2004). Inferential statistics refer to when an interpretation is made about population indices based on a sample randomly drawn from a population (Lombard, 2010; Welman, 2006). If one variable is involved it is called univariate analysis and if two variables are involved it is called bivariate analysis (Welman, 2006). If there are more than two variables involved in a study it is known as multivariate analysis (Welman, 2006). This study will use both descriptive and inferential statistics.

According to Welman (2006), measurement is the assignment of numbers to individuals to reflect differences between them in some characteristic. There are four levels of measurement, namely nominal, ordinal, interval and ratio. Nominal measurements are numbers assigned to individuals to distinguish between them, based on an attribute. Ordinal measurements or ordinal scales are rank ordered and are nominal by nature. Interval measurements have all the characteristics of both nominal and ordinal scales, but provide additional information regarding the degree of difference between individual data items within a group. Ratio scales as a measurement have the highest level of precision. In ratio measurement, there is a fixed and absolute zero point.

Once measurement is understood and the usability metrics chosen, a statistical test needs to be selected. The first factor to consider when choosing a statistical test is whether the data are normally distributed or not (Olivier, 2004). Should the data be found to have a normal distribution then parametric tests can be performed on the data. If the data are not normal then non-parametric tests will need to be performed (Olivier, 2004).

The second factor which determines which statistical test needs to be used is the number of variables in the study (Olivier, 2004). As has been previously mentioned, studies can be univariate, bivariate or multivariate.

The third factor that influences the choice of statistical test is the experimental design itself. The three most common experimental designs are independent subject design, matched subject design and finally repeated measures. In independent subject design, participants in a group are randomly assigned to the experimental conditions. The matched subject design requires the participants to be paired up and then randomly assigned to the experimental conditions. The repeated measures design has a number of measurements taken for each participant for a number of sessions for the same condition (Sharp, Rogers and Preece, 2007).

This study was concerned with potential differences between the abilities of participants in a group, measured over three sessions. In order to measure this, a repeated measures design was used, specifically a repeated measures ANOVA (Keselman, Algina and Kowalchuk, 2001). The approach assumed normality and sphericity, both of which needed to be tested and confirmed. To test normality the Shapiro-Wilk test was used. According to an in-depth study by Razali and Wah (2011), Shapiro-Wilk was determined to be the strongest normality test available. To measure sphericity the Mauchly's test was used.

A nonparametric alternative to repeated ANOVA is the Friedman test. However, the test lacks statistical power with small samples (Hill and Lewicki, 2005). Repeated ANOVAs are robust to violations of normality (Keselman, Algina and Kowalchuk, 2001), thus the test will be used regardless of the data's distribution.

If the data are found to be not spherical, two corrections can be applied to the degrees of freedom, namely the Greenhouse-Geisser correction or the Huynh-Feldt adjusted correction. If the Greenhouse-Geisser estimate is larger than 0.75 and sphericity has been violated, the more conservative Huynh-Feldt correction can be used (Keselman, Algina and Kowalchuk, 2001).

3.4 Summary

A research and design methodology was selected that has been proven and established by using a systematic approach. The study was an empirical study and required quantitative and qualitative measurements known as the mixed methods approach. From the methods that were available, an experiment was identified as a means to capture quantitative measurements and questionnaires for the qualitative measurements. Repeated usability testing was used for the experiment; thus, a repeated-measures ANOVA was determined to be suitable for data analysis.

Chapter 4 discusses the experimental design for this research, based on the research design and methodology discussed.

Chapter 4: Experimental Design

4.1 Introduction

The previous chapter outlined the research design and methodology that were used. This chapter expands this discussion by outlining the implementation of the experimental design used for this study.

The usability metrics used for this study are discussed in detail followed by a section explaining how the participant groups were classified. The experimental design used to measure the usability metrics is then discussed, followed by the test instrument software and hardware. The chapter closes with an overview of the protocol used by the evaluator for this study.

4.2 Hypothesis

Recall from the introduction chapter that a set of hypotheses were formulated based on the research questions and aims for this research:

- $H_{0,1}$: Exposure to a traditional input method does not influence a user's performance when manoeuvring a robot using a BCI.
- $H_{0,2}$: There is no difference in a user's performance when using a traditional input method compared to using a BCI when manoeuvring a robot.
- $H_{0,3}$: Repetitive use of a BCI has no effect on user performance when using a BCI.

The term *usability* used for this study incorporates aspects of *effectiveness*, *efficiency*, *learnability* and user *satisfaction*. For each usability test, a representative metric(s) needs to be used. These usability metrics will be discussed in the next section.

4.3 Usability Metrics

According to the QUIM model (Section 2.2.2.1), effectiveness, efficiency, learnability and user satisfaction are major factors of usability (Seffah et al., 2006). The QUIM model provided guidance on criteria that can be used with the usability factors. Figure 4.1 specifies the relationships between the factors and criteria in the QUIM model and provides guidance on which measurements would be suitable for the factors chosen for this study. Anxiety was measured as a means to help classify a participant into a group and was not drawn from the QUIM model but rather from the CAS theory.

Each factor used in this study will be discussed individually and the usability metrics derived from these factors are then motivated.

	Factors									
Criteria	Efficiency	Effectiveness	Satisfaction	Productivity	Learnability	Safety	Trustfulness	Accessibility	Universality	Usefulness
Time behavior	+			+						
Resource utilization	+			+						+
Attractiveness			+						+	
Likeability			+							
Flexibility		+	+					+	+	+
Minimal action	+		+		+			+		
Minimal memory load	+		+		+			+	+	+
Operability	+		+				+	+		+
User guidance			+		+			+	+	
Consistency		+			+	+		+	+	
Self-descriptiveness					+		+	+	+	
Feedback	+	+							+	+
Accuracy		+				+				+
Completeness		+				+				
Fault-tolerance						+	+			+
Resource safety						+				
Readability								+	+	
Controllability							+	+	+	+
Navigability	+	+					+	+	+	
Simplicity					+			+	+	
Privacy							+		+	+
Security						+	+			+
Insurance						+	+			
Familiarity					+		+			
Loading time	+			+					+	+

Figure 4.1: A matrix of criteria and factors in the QUIM model (Seffah et al., 2006).

4.3.1 Efficiency

Efficiency has been previously defined as the resources required from a user to achieve a task while using the system (Section 2.2.2.1). According to the QUIM model (Figure 4.1) the criterion *time behaviour* can be used to measure efficiency of a system. Therefore, for this study, participants were logged in seconds to measure how long they took to complete a usability task (Section 4.7.1).

4.3.2 Effectiveness

Effectiveness is the capability of the user to achieve a task with accuracy and completeness (Section 2.2.2.1). For the factor effectiveness, the criterion that will be used for this study is *accuracy*. Referring to the QUIM model (Figure 4.1), accuracy is the capability of a system to provide correct results or effects. Thus, accuracy can be measured using an error count. For this study this was done by measuring how many errors a user made during a usability test and was recorded whenever an out-of-bounds event occurred (Section 4.7.2).

4.3.3 Learnability

Learnability was defined as the ease with which the system can be mastered by the user over a short period of time (Section 2.5.1). Learnability was measured based on the characteristic *familiarity* in the QUIM model (Figure 4.1). The criteria minimal action and minimal memory load both fall under the factor learnability. Minimal action is the capability of software to help a user achieve the task and minimal memory load is the required information that a participant must keep in mind to achieve a task. These criteria were measured in this study by detecting variation in efficiency and effectiveness among the three usability tests. If variation was detected and a negative trend was observed, learning was said to have taken place (Section 4.7.3).

4.3.4 Satisfaction

Satisfaction is a subjective response from the participants of the study. Their opinions regarding use of the system is measured (Section 2.5.1). The criteria that were relevant to this study were *operability*, *capability* and *acceptability*. *Operability* was the amount of effort necessary to control the Emotiv, *capability* was how reliable and usable the participant felt the Emotiv was and *acceptability* indicated to what degree a participant felt it was safe to use the Emotiv to control a device. Subjective questions were asked of the participants who completed the study to measure these criteria. This was done in the form of an online questionnaire (Section 4.7.4) administered as a post-test questionnaire on completion of the study (Appendix B).

With the usability metrics required having been selected, a short discussion is required on how the participants were placed into the groups.

4.4 Determining Groups

Participants in the study were categorised into two groups: a group with low exposure to traditional input methods and a group with high exposure. For this study, the low exposure group was referred to as Group A and the high exposure group as Group B. Each participant was initially grouped, based on his/her geographical location, which was a rural university campus or an urban campus. Thereafter their anxiety towards computers was determined using the CAS questionnaire and their expertise rating with computers was measured. Measuring anxiety will be discussed followed by a discussion on expertise rating.

4.4.1 Measuring Anxiety

Computer anxiety is the fear a person has of computers when using a computer or considering the possibility of using a computer (Heinssen, Glass and Knight, 1987). The recruitment application form included a questionnaire designed to measure a participant's anxiety (Appendix A). This CAS questionnaire was developed by Marcoulides (1989) and is a twenty-point questionnaire categorised into two sections. The first section contains questions on general computer anxiety and is concerned with the anxiety stemming from direct experiences with the computer. The second section, equipment anxiety, has questions related to specific aspects of operating equipment. It was shown previously that the measured computer anxiety of a participant can be used to give an indication of a participant's background and was thus used to classify a participant by their exposure to traditional input methods (Section 2.3).

The questionnaire uses a five-point Lickert scale, which has negative responses placed to the left and positive responses on to right of the scale (Marcoulides, 1989; Olivier, 2004). This results in an anxiety score between 20 and 100. The questionnaire used in this study was a CAS that had been adjusted to a 6-point Lickert scale (Beelders, 2006; Blignaut, 1999; Chang, 1994).

4.4.2 Expertise Rating

On the recruitment questionnaire (Appendix A), participants were asked two questions to measure their expertise rating (Section 5.2). According to Rosson (1984), an expertise rating is determined by measuring the frequency and length of use of a activity. Therefore, a question measuring each of these factors was posed (Figure 4.2).

11. For how long have you been using computers?

[ ] Never [ ] 1 - 3 Months [ ] 3 - 6 months
[ ] 6 months - 1 year [ ] 1 year - 2 years [ ] 2 years - 3 years
[ ] 3 years - 5 years [ ] 5 years - 10 years [ ] More than 10 years

12. If you did not answer **Never** in question 11; How many times a week do you use a computer?

[ ] Once a week [ ] Twice a week [ ] Three times a week [ ] Four times a week [ ] Five times a week [ ] Daily [ ] Multiple times a day

Figure 4.2: Two demographic questions from recruitment questionnaire

For question 11, a value was assigned ranging from 0 for *Never* up until 7 for *More than 10 years*. Question 12 had values ranging from 0, which represented *Never* up until 7 for *Multiple times a day*. The expertise rating for a group was determined by multiplying the value of the total time a participant has used a computer (question 11) by the value of how often a week a participant utilised a computer (question 12). This produced an expertise rating with a minimum value of 0 and a maximum value of 42. An expertise rating within the range of 0 and 21 is classified as low exposure, while a rating within the range of 22 and 42 is classified as high exposure. Participants generally rated closely towards the range boundaries, with the exception of three participants in the rural group, who scored 28, 36 and 36, respectively. These participants were classified as high exposure, but were placed in the low exposure group, as they were rural participants.

The following discussion will explain the experiment structure used in this study.

4.5 Experiment

The experiment comprised of user tasks (Section 3.3.4) that had to be completed in a session according to seven predetermined levels on a test course. Each element of the experiment used in this study will be discussed in turn.

4.5.1 Task Structure

Each participant was tested on five different actions that formed the basis of the user tasks. These actions were based on assistive wheelchair systems such as the FRIEND system (Section 2.9). Specifically the actions tested were move *forwards*, *move backwards*, *rotate left*, *rotate right* and *switch*. The final action, *switch*, represented a peripheral on the wheelchair, such as a turning on a screen or moving an attached arm. Relevant actions to the study were the following:

- **Forward**: move the robot directly forwards.
- **Backwards**: move the robot directly backwards.
- **Turn Right**: rotate the robot 90 degrees on the spot to the right.
- **Turn Left**: rotate the robot 90 degrees on the spot to the left.
- **Switch**: switch control focus of the robot from the first robot (Alpha) to the second robot (Beta).

4.5.2 Session

A session for this study was the contact time between the evaluator and the participant and included the training time and the usability test time. Due to constraints on time and resources, it was necessary to limit a participant's time to a maximum of seven sessions. Within this limit, a participant was allowed to use a maximum of two sessions to train a single action. This decision was based on a study by Vourvopoulos and Liarokapis (2012), who utilised the Emotiv and reported a skill percentage of 45% for forward and backward actions with only one hour of training. Therefore, a training session between 45 and 90 minutes per action was believed to be enough time to achieve a skill percentage of above 50% and this guided the session design for this research. Once the action was trained to the satisfaction of the evaluator, the participant was required to perform a timed usability test based on the action. If the action was not trained to the satisfaction of the evaluator and the maximum time allowed (90 minutes) for sessions was reached, the skill percentage was noted and the participant automatically progressed to the next level. Usability tests were performed three times per action, allowing for the usability of the system to be verified.

Each action a participant was required to perform was called a level. For example, moving forwards was referred to as level 1. The levels are discussed in the following section.

4.5.3 Levels

The study was designed to have seven levels of difficulty that a participant needed to accomplish to complete the study (Table 4.1). The first five levels required the participant to learn an action using the Emotiv to the satisfaction of the usability evaluator. The last two levels tested the actions from the first five levels using two test courses and two robots. For the first five levels, the participant was allowed 30 minutes for training and 15 minutes for the usability testing. For levels 6 and 7, the entire session of 45 minutes was used for the usability tests in order to test the participant on all actions together.

Table 4.1 Task Levels

Level	Task Description	Time Per Test	Total Test Time	Skill Tested
1	Move the robot 50 cm forwards along Course A then stop.	5 min	15 min	Push
2	Move the robot 50 cm backwards along Course A then stop.	5 min	15 min	Pull
3	Rotate robot 90 degrees right.	5 min	15 min	Turn Right
4	Rotate robot 90 degrees left.	5 min	15 min	Turn Left
5	Switch control focus from one robot to another.	5 min	15 min	Switch
6	Move robot forwards 50 cm, stop then move robot backwards 50 cm along Course A. This must be done for both robots.	15 min	45 min	Push, Pull and Switch
7	Move robot forward 50cm, rotate robot 90 degrees right, move forwards 25cm, rotate robot 90 degrees left, move robot forwards 50 cm.	15 min	45 min	Push, Turn Right, Turn Left and Switch

However, the Emotiv system is limited to four available actions at any one time. Thus, two sets of usability tests needed to be conducted in order to test all the available actions. Level 6 tested the actions *move forwards*, *move backwards* and *switch*. Level 7 tested the actions *move forwards*, *rotate right*, *rotate left* and *switch*. The levels were tested using a custom designed course, which is discussed next.

4.5.4 Test Course

The goal for the test course was to represent each needed action to the participant clearly. The course also needed to allow two robots to move along the course simultaneously to accommodate the switch action. Figure 4.3 shows the first iteration of the obstacle course.

The design shown in Figure 4.3 was piloted using three volunteers. The general feedback from the participants revealed the course as confusing and difficult to follow. Their feedback was incorporated and the test course was modified and piloted with three different volunteers, resulting in the course shown in Figure 4.4. This version of the test course received positive feedback from the volunteers and was thus used for this study.

The course on the left (which has its borders coded with *1x*) of Figure 4.4 was known as Course A and was navigated by the robot designated Alpha. The second course on the right (which has the borders coded with *2x*) indicated the path for the robot designated Beta**.** The course was created on a series of A0-sized white poster boards bound together with tape. The borders of the Alpha course were created using red tape and the borders of the Beta course were created using green tape. Each robot came with a colour sensor and it was thought that when a robot moved out of the bounds of the course, this could be captured by simply detecting the correct colour with the sensor mounted on the front of the robot. However, it was discovered that the colour sensor was not sensitive enough to detect a change in colour accurately and was thus unreliable. To solve this problem the evaluator marked an out-of-bounds event on the session report to ensure that an error was reliably captured. In order to check where a robot went out of bounds accurately, each border was given a code which when crossed was marked on the test protocol sheet (Appendix C).

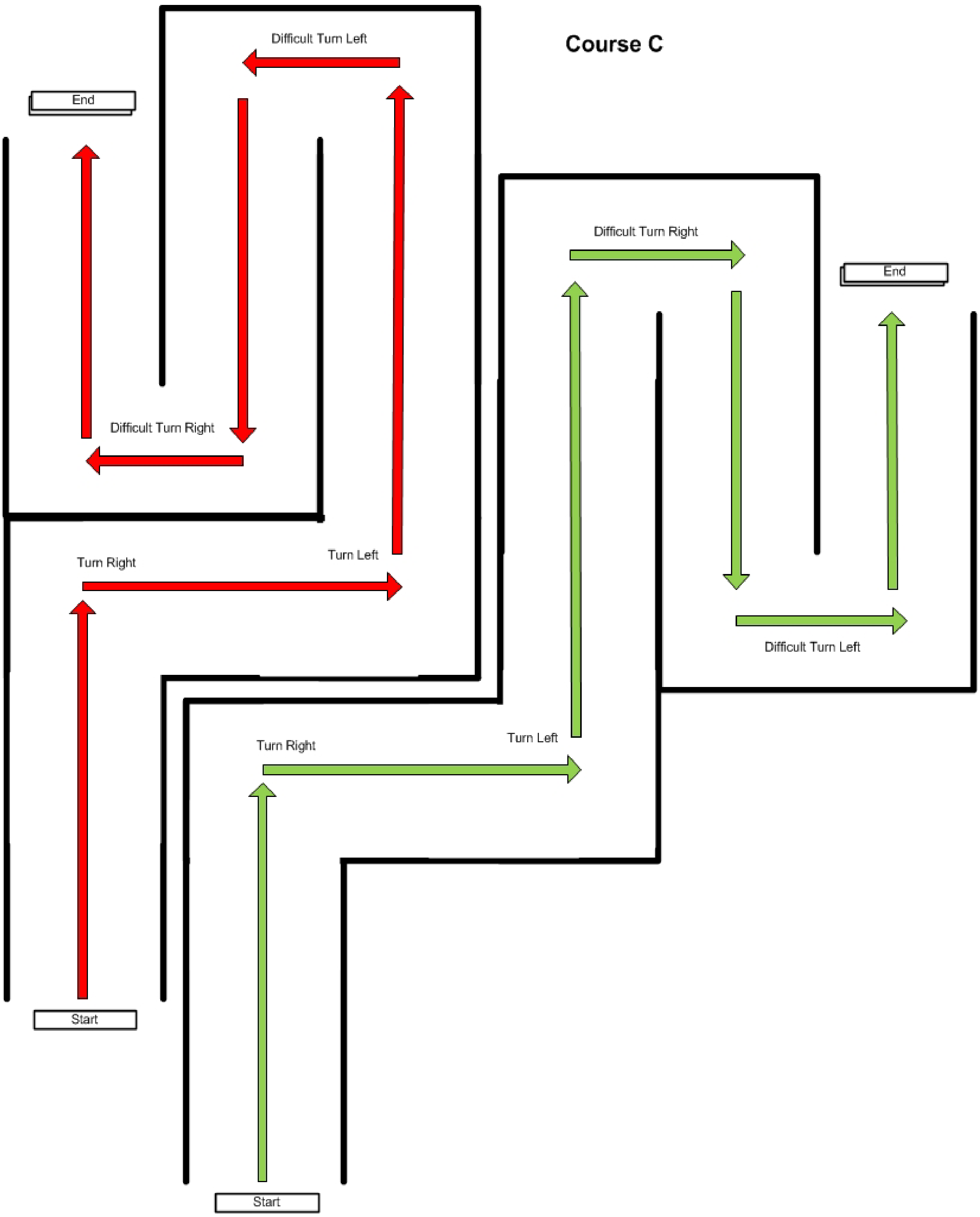


Figure 4.3: Early version of test course.

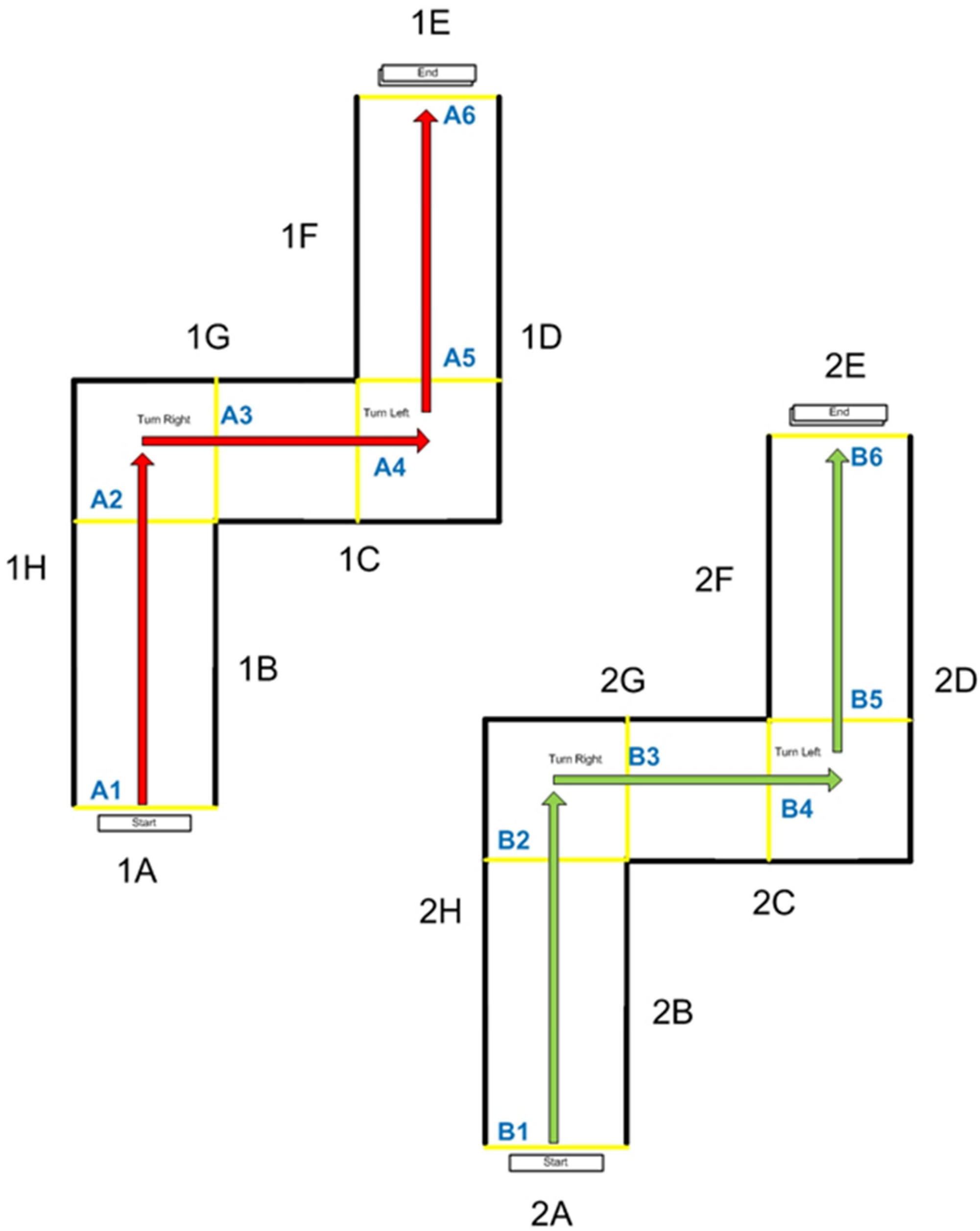


Figure 4.4: Test course used for this study.

The next section discusses the locations where the experiment was administered.

4.5.5 Test Location Descriptions

4.5.5.1 Qwaqwa

The location used for the usability tests and training sessions for the Group A participants (Section 4.4) was the conference room in the library building on the Qwaqwa Campus. The venue was not a usability laboratory; therefore, all recording equipment was brought in and set up before the start of the sessions. A desk and chair were set up for the evaluator and a chair for the participant. The test course was set up directly in front of the participant on the floor within full view of the evaluator. As mentioned previously, the two test courses were designed on a series of connected posters that could be folded out on a space on the floor. The same test course poster was used for both groups to ensure consistency between all participants in the study.

4.5.5.2 Bloemfontein

The location used for the usability tests and training sessions for the Group B participants (Section 4.4) was the Honours computer laboratory in the Department of Computer Science and Informatics on the Bloemfontein Campus. The venue was not a usability laboratory and was filled with equipment. A space was cleared in the centre of the laboratory with a chair set up for the participant with the test course positioned in front of him. The evaluator was seated at a desk that was a fixture in the laboratory within full sight of the participant and the test course.

The next section will discuss the test instrument used in this experiment.

4.6 Test Instrument

In order to achieve the objectives of the study, a system was needed that could produce an online control signal from a non-invasive BCI and store the results for offline analysis.

To do this, a system with three major components, namely a BCI headset, a robot and an application with the ability to capture the data and store it in a database was designed and developed (Figure 4.5).

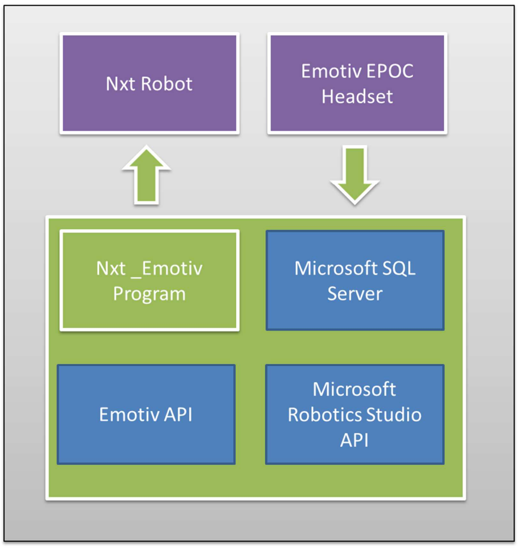


Figure 4.5: Application overview

4.6.1 Software

The software application used for testing consisted of three main components: the Emotiv control panel, a .Net application called Emotiv NXT Remote and a Microsoft-based database. The software suite included in the Emotiv package had a complete API (Application Programming Interface) available to the researcher. The API was utilised with Microsoft Robotics Studio (MRDS) to enable communication between the Emotiv and the robot.

4.6.1.1 *Emotiv Control Panel*

The Emotiv control panel (Figure 4.6) contains a suite of programs provided with the Emotiv to help the user access the functionality of the Emotiv headset (Emotiv, n.d.).

The control panel has a number of tabs that give feedback to the user on the state of the headset. The first tab gives direct feedback on connection quality for each of the 16 sensors used by the headset. The expressive tab is used to train and then detect muscle movements that result in an expression, such as smiling or frowning. The affective tab is used to monitor feelings of relaxation or frustration detectable by the Emotiv. The final tab controls the cognitive aspects of the device; this is where the software can be trained to associate a certain electrical pattern of participants' thoughts to a specific command.

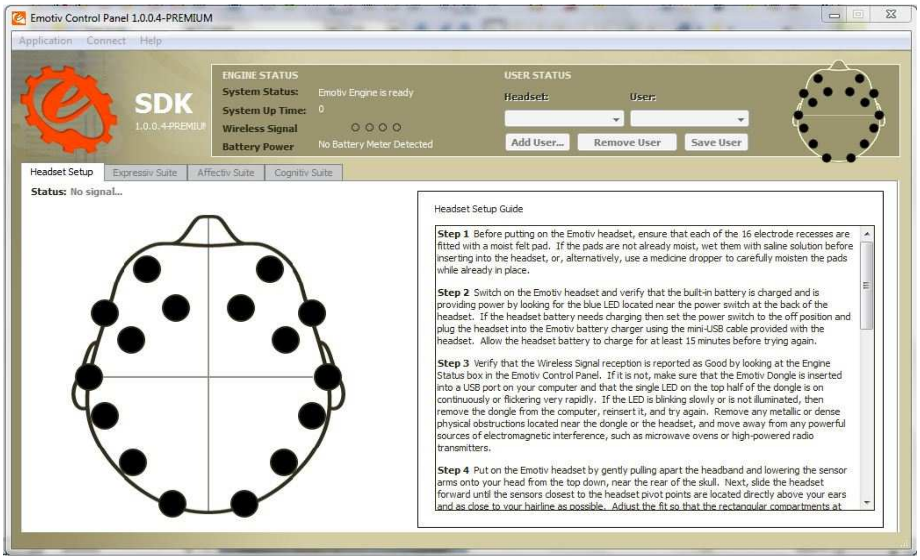


Figure 4.6: Emotiv Control panel

The first iteration of the system generated a key press event whenever a certain cognitive or affective event was triggered. At the time, it was thought that this event could be captured and a command subsequently generated for the robot. However, during the pilot test this method caused a noticeable lag for users of the system resulting in feelings of frustration. To resolve this problem an application was developed to access the Emotiv directly. This software is discussed in the next section.

4.6.1.2 Emotiv NXT Remote

The Emotiv NXT Remote (Figure 4.7) was developed to link the Emotiv EPOC headset to the Mindstorm NXT robots while capturing every user action into a database. The Microsoft Robotic Development Studio (MRDS) architecture and Emotiv API were utilised to communicate with the Mindstorm NXT within the application.

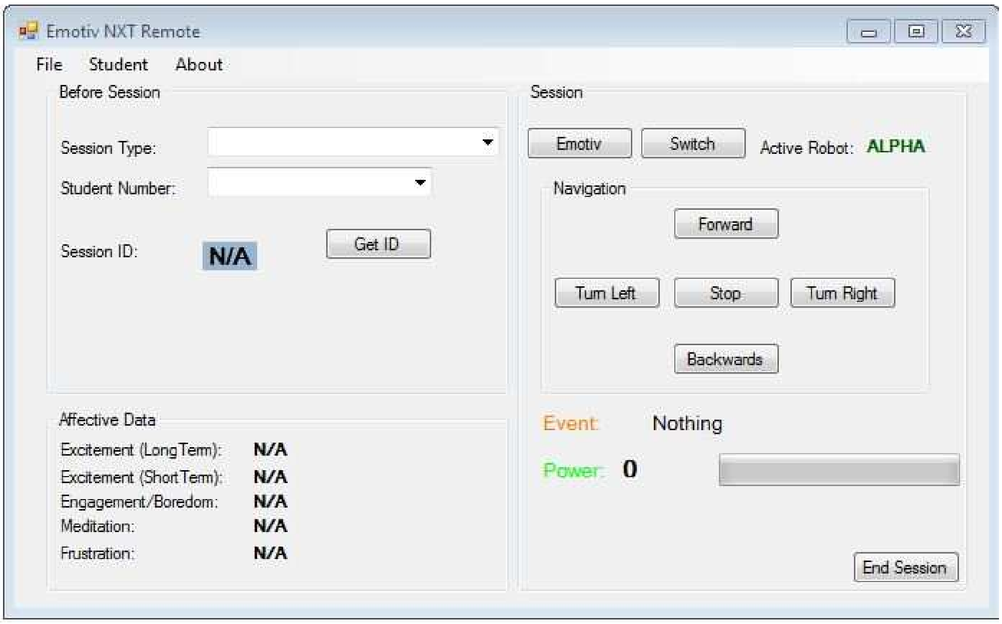


Figure 4.7: The remote application for the Emotiv

The remote application administered the individual training sessions and usability test sessions. During a session, feedback was given to the evaluator on the detected affective state of the participant as well as the cognitive action detected and the pattern match to the trained action. The application gave feedback on various affective aspects and indicated what cognitive action the user attempted (Figure 4.7). Each cognitive and affective aspect was captured into a Microsoft SQL database (Figure 4.8).

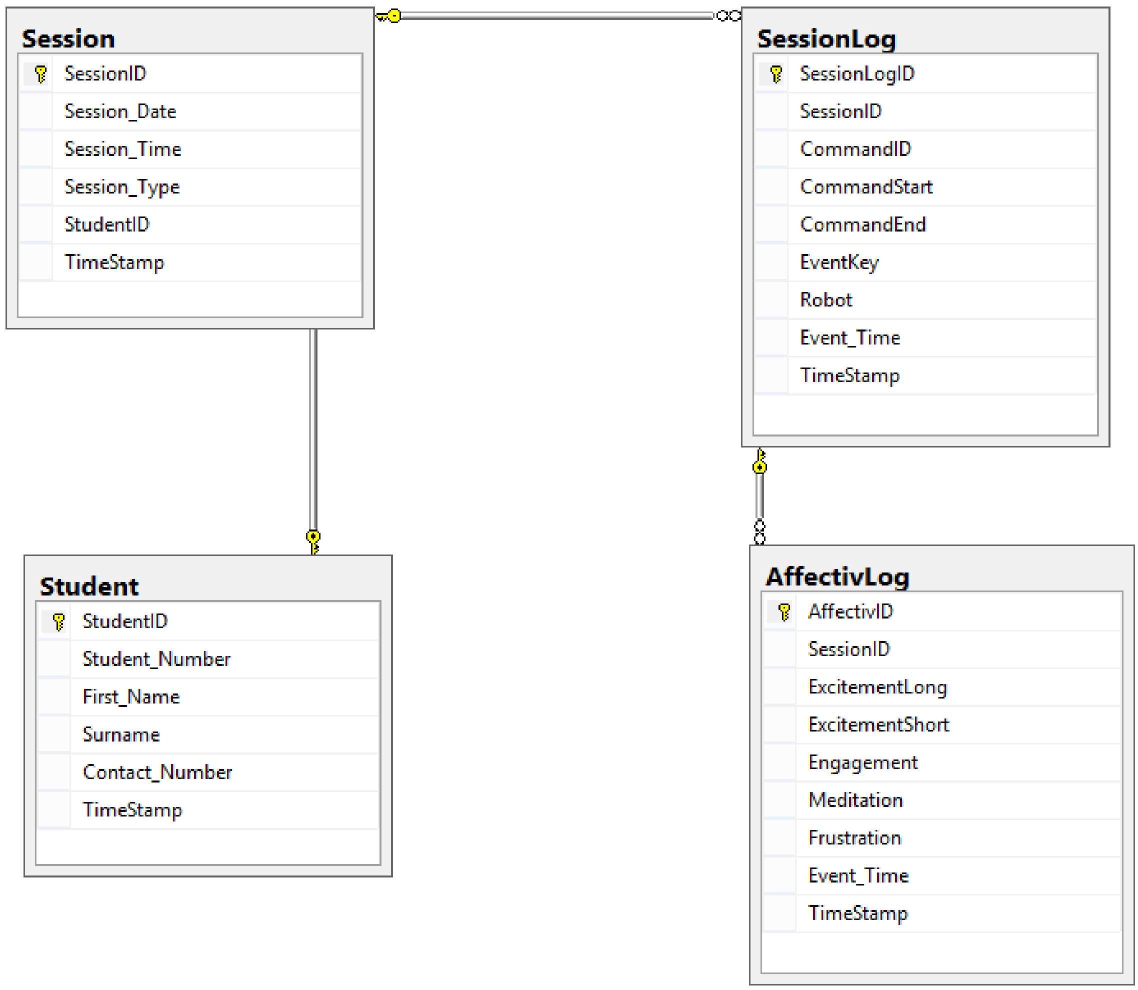


Figure 4.8: ERD for database used to capture data

4.6.2 Hardware

As previously discussed (Section 2.9.3), the BCI headset used for this study was the Emotiv. The robots selected to be controlled by the headset for the study were two off-the-shelf programmable robots called the Mindstorm NXT (Figure 4.9). The robot is cost effective, easy to use and is fully programmable with Microsoft programming languages. The main hardware component of the NXT is a rectangularly shaped computer called the intelligent NXT brick. The brick has a 32-bit ARM7 processor and 64kb of RAM. The computing power available to the robot is suitable for basic low-level tasks. The different components are plugged into the brick using a RJ12 connector. To overcome the limited processing power, the NXT robot was slaved to a Windows based personal computer via a wireless signal.

The next section will discuss how the test instrument was used to capture the usability metrics for this study.

Figure 4.9: Pair of Mindstorm NXT robots used for this study.

4.7 Measurements

This section will outline how this study measured *efficiency, effectiveness, learnability* and *satisfaction*.

4.7.1 Measuring Efficiency

As mentioned in Section 4.3.1, *efficiency* was measured by recording the time it took a participant to complete a usability test. The evaluator first selected a session type and the correct participant number from the dropdown lists. This identified who was taking part and what level they were attempting. The session was started when the evaluator pressed the *Get ID* button on the form (Figure 4.7). From that point onwards, every cognitive command used to navigate the robot was recorded into a database in real time. The session ended when the *End Session* button was pressed by the evaluator. The timestamps between the start and end of the session were compared and the difference between the two was stored as the completion time for the usability test. This procedure was used for usability tests as well as training sessions to acquire the efficiency measurement.

4.7.2 Measuring Effectiveness

Effectiveness was measured by recording an error whenever the robot was guided across the borders of the test course (Appendix C and Appendix D) (Section 4.5.4). This event was manually recorded by the session evaluator on the session protocol sheet (Appendix E) for later analysis. The border that the robot crossed was marked on the sheet with the corresponding code. For example, if the robot to the left test course (Figure 4.10) crossed the obstacle course to the left, the evaluator marked the sheet with *1D*. The robot was considered to have crossed the border when more than half the robot's body had crossed over the borderline.

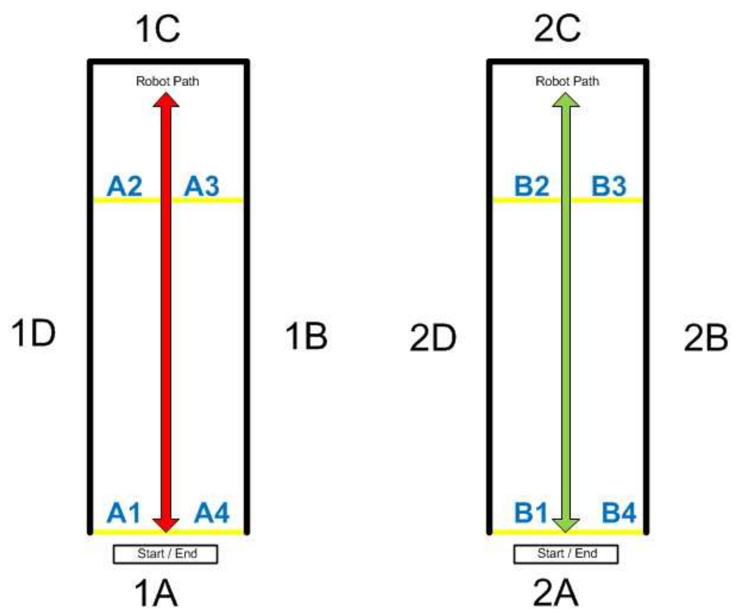


Figure 4.10: Error guidelines for Course A

4.7.3 Measuring Learnability

Learnability over the short term was measured by detecting variance between the usability tests for *efficiency* and *effectiveness* over three trials. A trend of improved performance would indicate that learning took place.

4.7.4 Measuring Satisfaction

Satisfaction was measured via an online questionnaire that was administered to the participants who completed the study. The first five questions were open questions that asked the participants what imagery they used to generate a specific command (Appendix B). The last four questions used a five-point Likert scale to measure a participant's reaction to the system subjectively, how difficult the system was to learn, the system capabilities and how acceptable the participant deemed the Emotiv to be for use in similar situations (Appendix B).

The final section of this chapter will describe the protocol used for the experiment.

4.8 Protocol

4.8.1 Test Administration Protocol

Each participant was assigned a letter of the alphabet for identification and was asked to attend seven sessions over a period of no more than eight weeks. Each session was in a one-on-one setup between the evaluator and the participant in a safe and comfortable environment (Section 4.5.5).

4.8.2 Training Protocol

Each session was designed to take no longer than 45 minutes. Of the 45 minutes, 30 minutes were used for the training in the session, with the other 15 minutes used for the usability tests. The exception to this protocol was levels 6 and 7; these levels were longer usability tests that took up to 45 minutes in total. During a training session, the evaluator monitored the affective aspects of the participant and tried to keep the participant relaxed and focused.

The Emotiv control interface had a percentage indicator of how proficient a person was when trying to generate a certain command. When training a command, the software required the participant to keep the thought in focus for ten seconds. Over this period, the control panel executed the learning algorithm previously discussed in Section 2.9.3 to detect the EEG pattern matching the imagery generated by the participant. The results were then reported to the evaluator as a percentage. Once the training reached an acceptable percentage, the action was considered trained and the participant was then tested. The participant also automatically progressed to the next level if they had used two sessions to train an action without reaching an acceptable percentage.

4.8.3 Usability Testing Protocol

The usability tests were all performed in sets of three for each trained action. With the exception of level 6 and 7, all usability tests fitted into a time slot of 15 minutes. For each usability test, a maximum time was given to complete the test, five minutes for levels 1 to 5, 15 minutes for levels 6 and 7. If the allotted time was expended and the participant had not completed the task, the evaluator recorded the progress up to that point and ended the test. During the test, the evaluator observed the session, but did not interfere or distract the participant.

4.9 Summary

The experimental design used for this study was discussed in this chapter. The usability metrics were discussed as well as how these metrics were measured. The metrics efficiency and effectiveness were captured via a custom-designed software application called the Emotiv NXT remote. Learnability was measured by detecting variance between the usability tests for efficiency and effectiveness. The metric satisfaction was captured via a post-test questionnaire.

The following chapter will analyse the data captured during the course of the study.

Chapter 5: Experiment Analysis

5.1 Introduction

The previous chapter determined and motivated the experimental methodology that was used for this study. This chapter will analyse the data captured from the experiment. The chapter starts with an analyses and discussions on how participants were classified for this study. The efficiency and effectiveness results are then analysed and discussed, followed by a discussion on the participant's satisfaction. The chapter ends with a final, overall discussion based on the analyses of the usability metrics.

5.2 Participants

The participants were recruited from two campuses based on their geography. A participant's exposure to traditional input methods (keyboard) was verified using their expertise rating and computer anxiety score. Subsequently, the participant was placed into one of two groups. As previously mentioned (Section 4.4), low exposure participants were placed into Group A and high exposure participants into Group B.

A group's computer anxiety (Section 4.4.1) was thought to be an indicator of the group participants' exposure to traditional input methods, in this case a keyboard. To confirm this, a two-tailed t-test was performed to check the assumption that the results of the computer anxiety scale were related to the group's exposure to traditional input methods. The null hypothesis tested for this purpose was the following:

- H_0: There is no significant difference between the computer anxiety factors of Group A and Group B.

Table 5.1 indicates the minimum and maximum anxiety results that were possible as calculated using the factor loadings from Marcoulides (1989). Group A had a higher mean ($\mu = 36.31$, $s = 12.47$) than Group B ($\mu = 27.77$, $s = 4.38$) which suggested that Group A in general felt more anxious when working with computers.

However, the t-test results for the general section (t (5) = 0.41, $p > 0.05$) and equipment section (t (7) = 0.31, $p > 0.05$) indicated that there was no significant difference in computer anxiety between the two groups for either categories. Therefore, the null hypothesis was not rejected and computer anxiety was not significantly different between the two groups. Therefore, the computer anxiety results could not be used as a classification for participants. Additionally, any differences observed between the groups will not be because of a difference in anxiety levels.

Table 5.1: Computer Anxiety score breakdown

Anxiety subsection	Minimum anxiety score	Maximum anxiety score
General	10.06	60.36
Equipment	3.69	22.14
Overall	13.75	82.50

The participants were then compared on their expertise rating (Section 4.4). Group A had an average expertise rating of 16.45, while Group B had an average expertise rating of 41.25. In general, the individual scores for Group A were lower than Group B. Thus, Group A shared a low expertise rating and Group B shared a high expertise rating, collectively.

Based on these results, it could be said that the groups were differentiated by their exposure to computers. As computers commonly use a mouse and keyboard, the groups could be differentiated by their use of traditional input methods. As a tool for classification, the recruitment questionnaire had some shortfalls. The questionnaire was designed for this study so the validity of the results could not be confirmed; additionally, the questionnaire did not distinguish between the different types of computers, such as mobile devices or personal computers (PCs).

On completion of the study, Group A had been reduced to ten participants and Group B to eight participants. The low retention rate for the study resulted in Group A having six females and four males and Group B having three females and five males by the end of the study.

As previously discussed (Section 4.5.3), a participant was not allowed to progress to the next level of testing unless a satisfactory training percentage was achieved or the participant had used up two sessions of training. The study length per participant was limited to a maximum of seven sessions. Therefore, it was possible that a participant could not have made it further than level 3 for usability tasks (Table 5.2). It is interesting to note that no participants made it to level 7, with only two participants from Group A and one participant from Group B reaching level 6. The fact that only seven participants are reflected for Group B level 2 is attributable to a recording anomaly, which resulted in a measurement being discarded, because the test instrument continued recording data after the final usability test had been completed.

Table 5.2: Number of participants per level

	Group A	Group B
Level 1	10	8
Level 2	10	7*
Level 3	10	8
Level 4	8	7
Level 5	5	2
Level 6	2	1
Level 7	0	0

*Data for a subject were not recorded correctly and therefore had to be excluded

5.3 Comparative Analysis of Efficiency

This section discusses the differences in efficiency between Group A and Group B when using the Emotiv and a keyboard to navigate a robot across a test course. Recall that efficiency was measured by the time taken to complete a usability task, as discussed in Section 4.3.1. Before proceeding with the statistical analysis, it had to be determined whether the data were normally distributed. Each normality test used the following hypothesis:

- H_0: The time taken to complete the test course follows a normal distribution.

The time session data were first tested for normality and were found to be not normal. The data were then transformed to 1/time, as this is often normally distributed, and then tested again for normality. The 1/time normality results are reported in Table 5.3 and used for this study. As determined in Section 3.3.5, the normality test that was best suited for the study was the Shaprio-Wilk test, with an α–value of 0.05. Aside from level 4 and 5, the data did not follow a normal distribution. As mentioned in Section 3.3.5, the nonparametric equivalent to a repeated-measure ANOVA is the Friedman test. The test was not used for this study, as the test lacked statistical power with small samples. Fortunately, repeated measures ANOVAs are robust to violations of normality, thus allowing for the test to be used under these conditions (Keselman, Algina and Kowalchuk, 2001).

Table 5.3: Normality tests for Efficiency

	Session	**Result**
Level 1	Session 1	W= 0.878, $p < 0.05$*
	Session 2	W= 0.909, $p < 0.05$*
	Session 3	W= 0.832, $p < 0.05$*
Level 2	Session 1	W= 0.898, $p < 0.05$*
	Session 2	W= 0.874, $p < 0.05$*
	Session 3	W= 0.877, $p < 0.05$*
Level 3	Session 1	W= 0.924, $p < 0.05$*
	Session 2	W= 0.911, $p < 0.05$*
	Session 3	W= 0.915, $p < 0.05$*
Level 4	Session 1	W= 0.965, $p > 0.05$
	Session 2	W= 0.928, $p > 0.05$
	Session 3	W= 0.963, $p > 0.05$
Level 5	Session 1	W= 0.966, $p > 0.05$
	Session 2	W= 0.896, $p > 0.05$
	Session 3	W= 0.964, $p > 0.05$
Level 6	Session 1	W= 0.732, $p < 0.05$*
	Session 2	W= 0.787, $p < 0.05$*
	Session 3	W= 0.726, $p < 0.05$*

*Results are significant

A repeated-measures ANOVA assumes that a data sample has sphericity; consequently, the sphericity of the data had to be verified. If sphericity was found to be violated, an adjusted F-ratio could be used by adjusting the degrees of freedom using the Greenhouse-Geisser Epsilon or the Huynt-Feldt Epsilon factor (Keselman, Algina and Kowalchuk, 2001).

For this study violations of sphericity were adjusted using Greenhouse-Geisser, as it was the more conservative choice available (Keselman, Algina and Kowalchuk, 2001). When testing for sphericity, the Mauchly's test was used with a α–value of 0.05. The test used the following hypothesis:

- H_0: The covariance matrix is spherical for the data sample.

Levels 1, 3, 4 and 5 (Table 5.4) returned results of non-significance; therefore, for these levels the means of the covariance matrix were spherical and the adjusted factor was not required. However, levels 2 and 6 both violated sphericity. It was thus necessary to use an adjusted F-ratio using the Greenhouse-Geisser Epsilon.

Table 5.4: Mauchly's tests for Efficiency

Level Tested	**Result**
Level 1	$\chi^2 = 1.269$, $p > 0.05$
Level 2	$\chi^2 = 10.304$, $p < 0.05$*
Level 3	$\chi^2 = 0.999$, $p > 0.05$
Level 4	$\chi^2 = 4.998$, $p > 0.05$
Level 5	$\chi^2 = 5.867$, $p > 0.05$
Level 6	$\chi^2 = 0.000$, $p < 0.05$*

*Significant Result

With sphericity evaluated, the data were then tested using repeated measures ANOVAs to answer the general hypothesis for efficiency for each level:

- $H_{0,1}$: Exposure to traditional input methods does not influence the time taken when manoeuvring a robot using the Emotiv.
- $H_{0,2}$: There is no difference in the time taken to complete a task when using a keyboard compared to using the Emotiv when manoeuvring a robot.
- $H_{0,3}$: Repetitive use of the Emotiv has no effect on the time taken to complete a task when using the Emotiv.

The group factor result (Table 5.5) indicated that for all level tasks the group had no significant effect on the time taken to complete a task. Thus the null hypothesis $H_{0,1}$ was not rejected and exposure to traditional input methods does not influence efficiency when manoeuvring a robot using the Emotiv.

Table 5.5: Repeated measures ANOVAs usability test results for the six levels

Factor	**Level Tested**	**Result**
Short-term learnability	Level 1	$F_{2, 52} = 3.726$, p < 0.05*
	Level 2	$F_{1.518,42.512} = 0.137$, p > 0.05^
	Level 3	$F_{2, 52} = 1.496$, p > 0.05
	Level 4	$F_{2, 46} = 0.268$, p > 0.05
	Level 5	$F_{2, 16} = 2.148$, p > 0.05
	Level 6	$F_{0.5, 1} = 1.359$, p > 0.05^
Group	Level 1	$F_{1, 26} = 0.054$, p > 0.05
	Level 2	$F_{1, 28} = 0.275$, p > 0.05
	Level 3	$F_{1, 26} = 1.251$, p > 0.05
	Level 4	$F_{1, 23} = 0.153$, p > 0.05
	Level 5	$F_{1, 8} = 1.393$, p > 0.05
	Level 6	$F_{1, 2} = 2.680$, p > 0.05
Input Method	Level 1	$F_{1, 26} = 0.011$; $p < 0.01$*
	Level 2	$F_{1, 28} = 81.657$; $p < 0.01$*
	Level 3	$F_{1, 26} = 46.675$; $p < 0.05$*
	Level 4	$F_{1, 23} = 86.362$; $p < 0.01$*
	Level 5	$F_{1, 8} = 21.958$; $p < 0.05$*
	Level 6	$F_{1, 2} = 1719.510$; $p < 0.05$*

*Significant Result

^Adjusted result using Greenhouse-Geisser

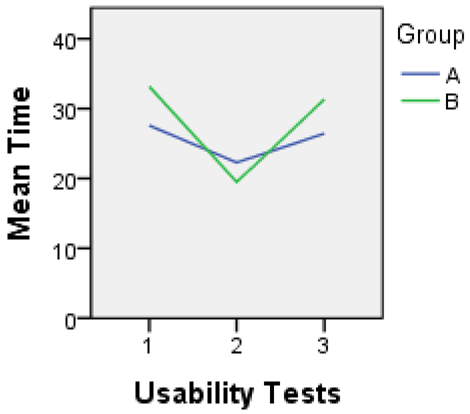


Chart 5.1: Mean time taken for level 1 using an Emotiv

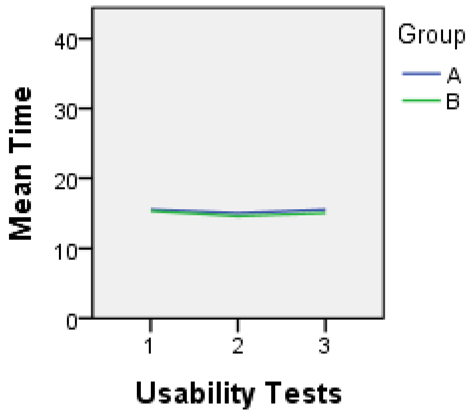


Chart 5.2: Mean time taken for level 1 using a keyboard

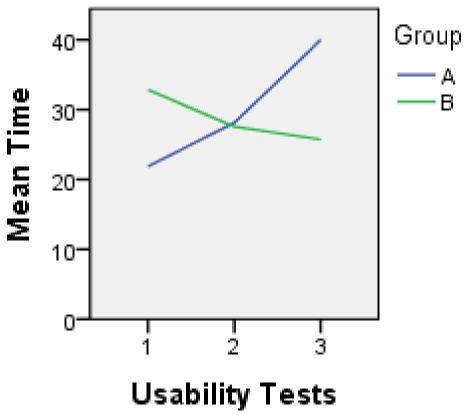


Chart 5.3: Mean time taken for level 2 using an Emotiv.

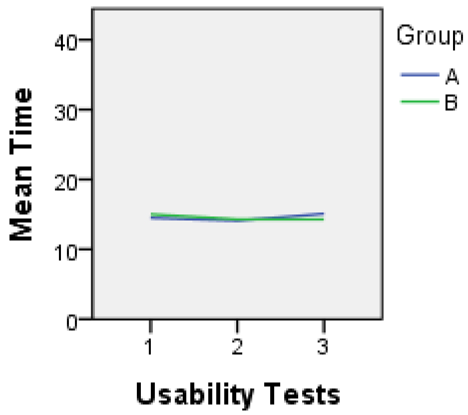


Chart 5.4: Mean time taken for level 2 using a keyboard.

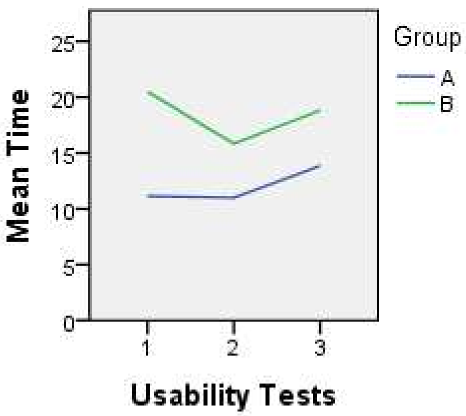


Chart 5.5: Mean time for level 3 using an Emotiv

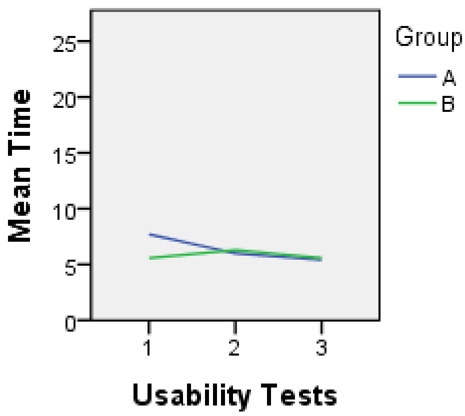


Chart 5.6: Mean time taken for level 3 using a keyboard.

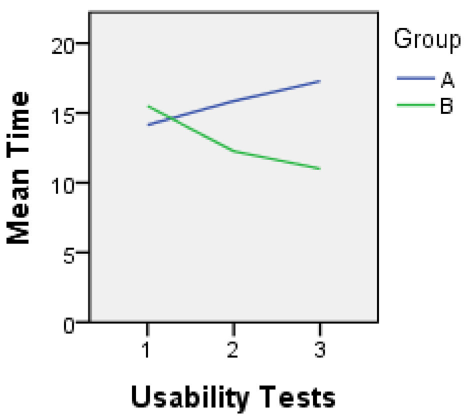


Chart 5.7: Mean time taken for level 4 using an Emotiv.

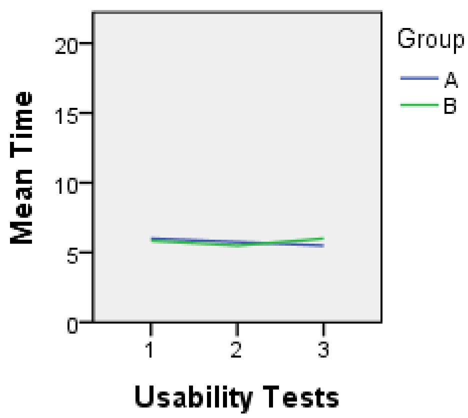


Chart 5.8: Mean time taken for level 4 using a keyboard.

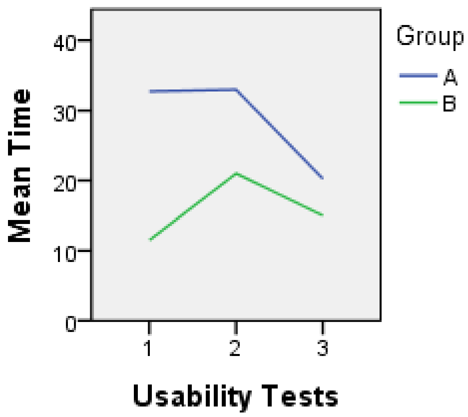


Chart 5.9: Mean time taken for level 5 using an Emotiv

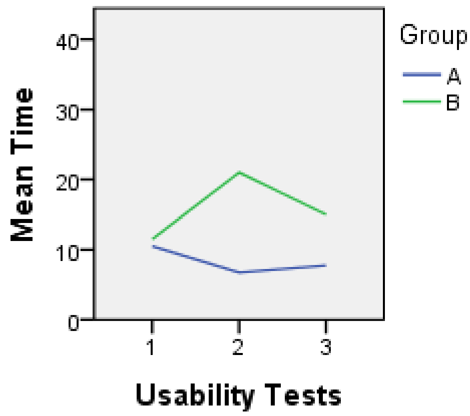


Chart 5.10: Mean time taken for level 5 using a keyboard

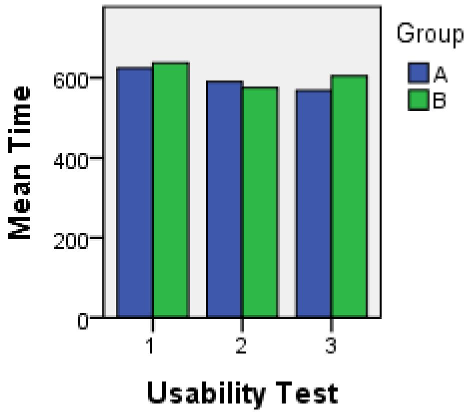


Chart 5.11: Mean time taken using the Emotiv on level 6

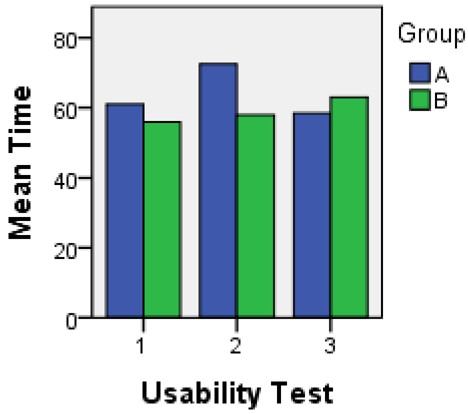


Chart 5.12: Mean time taken using the keyboard on level 6

However, the input method (Table 5.5) was found to have a significant impact on the time taken to complete a usability test. Therefore the null hypothesis $H_{0,2}$ was rejected and there was a difference in the time taken to complete a task when using a keyboard compared to using a Emotiv when manoeuvring a robot.

The factor short-term learnability in Table 5.5 indicated whether there was significant variance between the usability tests, which could indicate increased performance. There was no evidence of improvement between the sequential usability tests for levels 3 (Chart 5.5, Chart 5.6), 4 (Chart 5.7, Chart 5.8) and 5 (Chart 5.9, Chart 5.10). However, there was a significant difference between the usability test completion times for level 1. Chart 5.2 indicates no variance when using the keyboard to complete the usability tests. From the appearance of Chart 5.1, it can be surmised that the variation detected was caused by the performance difference using the Emotiv between session 1 and session 2, followed by a decreased performance in session 3. It was clear from the figure that there was no trend of improved performance as a learning effect would plot as a negative trend.

Although the usability test factor did not return significance for level 6 (Table 5.5), it was the first time that participants had been required to navigate the robots using commands simultaneously; therefore, the level 6 graphs were analysed for interest sake. No significant difference was detected between the usability tests and the figures indicated that there was no difference between the three usability tests for both groups who used the Emotiv (Chart 5.11) or the keyboard (Chart 5.12).

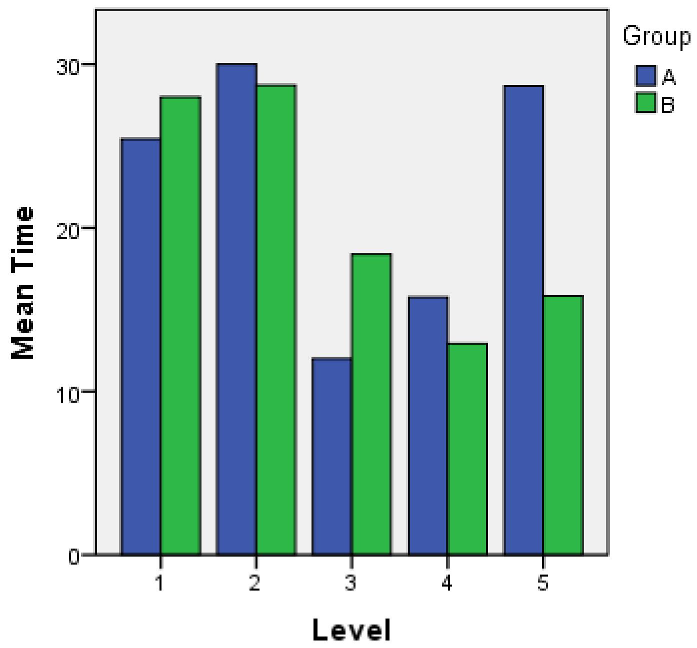


Chart 5.13: Mean time taken to complete a usability test using the Emotiv

Looking at a broader graph for all the levels (Chart 5.13), it was interesting to note that at level 1 Group A outperformed Group B with the *move forwards* task. Then, at level 2, Group B outperformed Group A with the *move backwards* task. The same pattern repeated itself between the groups for levels 3 and 4. As the levels increased, the participants had more commands available to them. According to Obermaier, Neuper, Guger and Pfurtscheller (2001), the more mental commands an individual has the more complex the problem is for the participant. Therefore, as the participant advanced up the levels in the study, the usability tests became more difficult. It was also possible that the disparity between the groups stemmed from the effect of the violation of a person's preformed schema of how an interface works. In cognitive theory, it was theorised that a person creates a best practices schema on how to work an interface. If a new interface does not match the pre-existing schema it can cause disorientation for the participant, resulting in computer anxiety and reduced performance (Chalmers, 2003). The use of the Emotiv was very different to using a keyboard; therefore, so the urban Group B who had high exposure to traditional inputs initially had reduced performance, compared to Group A.

Once the group developed a working schema the group's performance improved. This conclusion was further supported by the work of Mach, Hunter and Grewal (2010) who has found that if the newer interface differs significantly a new schema was formed, resulting in a different pattern of synchronisation when recorded using an EEG.

Considering all the evidence, the null hypothesis $H_{0,3}$ for efficiency was not rejected and repetitive use of the Emotiv has no effect on the time taken to complete a task when using a Emotiv.

5.4 Comparative Analysis of Effectiveness

This section discusses the differences in effectiveness between Group A and Group B when using the Emotiv or a keyboard to navigate a robot across a test course. As discussed in Section 4.3.2, effectiveness was measured by the errors a participant made when completing a usability task. Before proceeding with the analysis, it had to be determined whether the data were normally distributed using the Shaprio-Wilk test. The results for all the levels are reported in Table 5.6 and indicated that the level data did not follow a normal distribution, with the exception of level 5. There was no variance for the level 5 data and thus no statistical analysis could be performed.

As was discussed previously, repeated measures ANOVAs are robust to violations of normality. However, the data must still be tested for sphericity. This data were tested using Mauchly's test and the results are reported in Table 5.7. The data for levels 3, 4 and 6 violated sphericity and were adjusted using the Greenhouse-Geisser Epsilon.

With sphericity confirmed, the data were then tested using repeated measures ANOVA to answer the general hypothesis for effectiveness for each level:

- $H_{0,1}$: Exposure to traditional input methods does not influence the errors made when manoeuvring a robot using the Emotiv.
- $H_{0,2}$: There is no difference in the errors made when using a keyboard compared to using the Emotiv when manoeuvring a robot.
- $H_{0,3}$: Repetitive use of the Emotiv has no effect on the errors made for an action when using the Emotiv.

Table 5.6 Normality tests for Effectiveness

	Session	**Result**
Level 1	Session 1	W= 0.485, $p < 0.05$*
	Session 2	W= 0.451, $p < 0.05$*
	Session 3	W= 0.366, $p < 0.05$*
Level 2	Session 1	W= 0.295, $p < 0.05$*
	Session 2	W= 0.527, $p < 0.05$*
	Session 3	W= 0.378, $p < 0.05$*
Level 3	Session 1	W= 0.255, $p < 0.05$*
	Session 2	W= 0.485, $p < 0.05$*
	Session 3	W= 0.322, $p < 0.05$*
Level 4	Session 1	W= 0.188, $p < 0.05$*
	Session 2	W= 0.286, $p < 0.05$*
	Session 3	W= 0.287, $p < 0.05$*
Level 5	Session 1	No Result
	Session 2	No Result
	Session 3	No Result
Level 6	Session 1	W= 0.616, $p < 0.05$*
	Session 2	W= 0.665, $p < 0.05$*
	Session 3	W= 0.739, $p < 0.05$*

*Results are significant

Table 5.7: Mauchly's test for Effectiveness

Level Tested	Result
Level 1	$\chi^2 = 0.941$, $p > 0.05$
Level 2	$\chi^2 = 0.739$, $p > 0.05$
Level 3	$\chi^2 = 16.240$, $p < 0.05$*
Level 4	$\chi^2 = 0.0$, $p < 0.05$*
Level 5	No Result
Level 6	$\chi^2 = 5.221$, $p < 0.05$*

*Significant Result

The group factor indicated that for all levels the group had no significant effect on the errors made when completing a task (Table 5.8). Therefore the null hypothesis $H_{0,1}$ for effectiveness was not rejected and exposure to traditional input methods does not influence the errors made when manoeuvring a robot using the Emotiv.

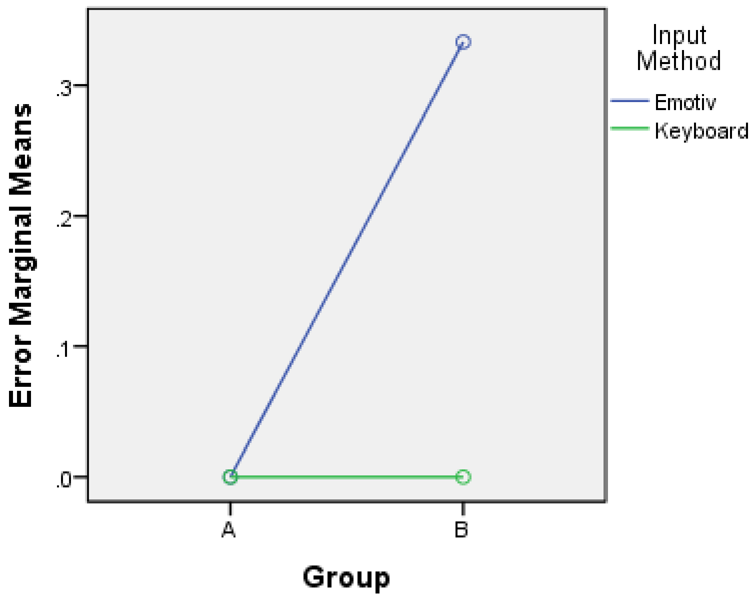


Chart 5.14: Mean error comparison of level 4 for both control methods

However, the input method (Table 5.8) was found to have a significant impact on the errors made when completing a task for levels 1, 2, 3 and 6. Considering Chart 5.14, Group A made no errors with either input method while Group B made a few errors with the Emotiv and none while using the keyboard. The fact that Group A made no errors for both input methods likely caused the repeated measures ANOVA result to return a non-significant result. Aside from level 4, the null hypothesis $H_{0,2}$ for effectiveness was rejected and therefore there was a difference in the errors made when using a keyboard, compared to using a Emotiv when manoeuvring a robot. Thus, a user is likely to make more errors with an Emotiv than with a keyboard.

Table 5.8: Repeated measures ANOVAs usability test results for the six levels

Factor	Level Tested	Result
Short- term learnability	Level 1	$F_{2, 62} = 0.383$, $p > 0.05$
	Level 2	$F_{2,56} = 2.520$, $p > 0.05$
	Level 3	$F_{1.4, 41.993} = 5.528$, $p < 0.05$^*
	Level 4	$F_{1, 24} = 1.371$, $p > 0.05$
	Level 5	No Result
	Level 6	$F_{1.003, 2.005} = 1.710$, $p > 0.05$
Group	Level 1	$F_{1, 31} = 0.008$, $p > 0.05$
	Level 2	$F_{1, 28} = 1.956$, $p > 0.05$
	Level 3	$F_{1, 30} = 0.099$, $p > 0.05$
	Level 4	$F_{1, 24} = 3.429$, $p > 0.05$
	Level 5	No Result
	Level 6	$F_{1, 2} = 0.334$, $p > 0.05$
Input Method	Level 1	$F_{1, 31} = 10.462$; $p < 0.01$*
	Level 2	$F_{1, 28} = 18.369$; $p < 0.01$*
	Level 3	$F_{1, 30} = 6.363$; $p < 0.05$*
	Level 4	$F_{1, 24} = 3.429$; $p > 0.05$
	Level 5	No Result
	Level 6	$F_{1, 2} = 9185.470$; $p < 0.05$*

*Significant Result

^Adjusted result using Greenhouse-Geisser

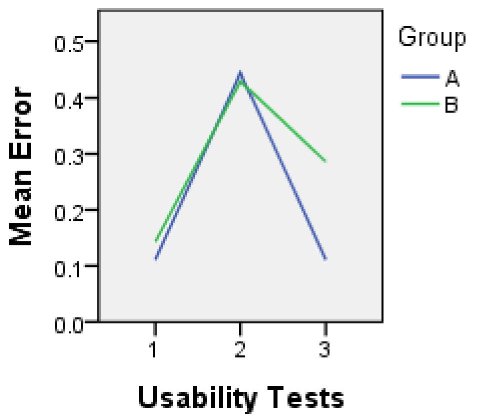


Chart 5.15: Mean error rate for level 1 using the Emotiv

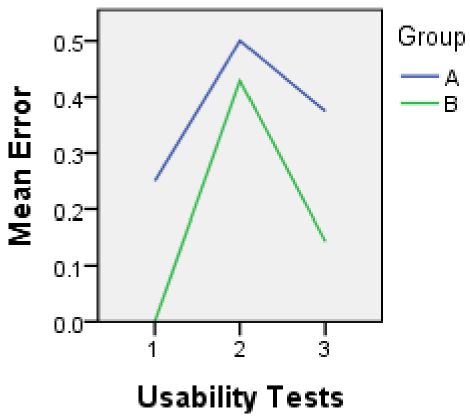


Chart 5.16: Mean error rate for level 2 using the Emotiv

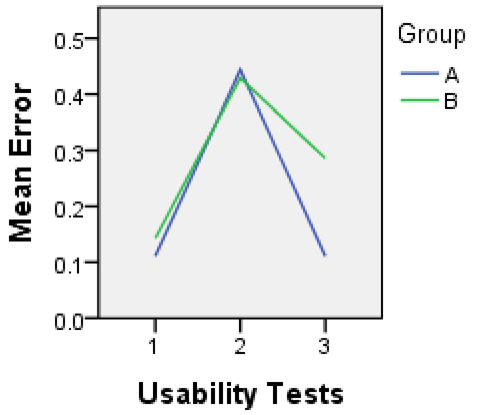


Chart 5.17: Mean error rate for level 3 using the Emotiv

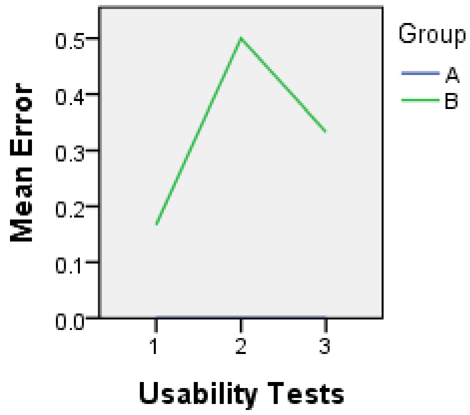


Chart 5.18: Mean error rate for level 4 using the Emotiv

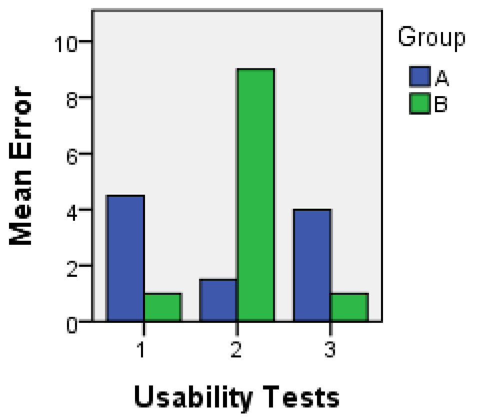


Chart 5.19: Error rate mean for level 6 using the Emotiv

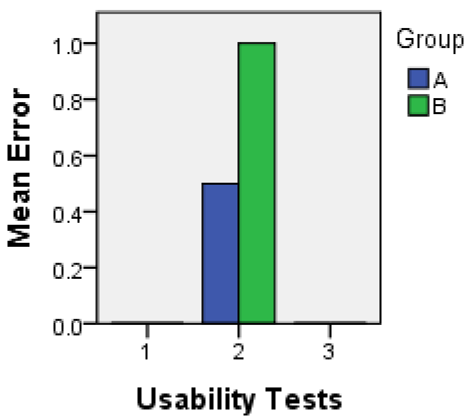


Chart 5.20: Error rate mean for level 6 using the keyboard

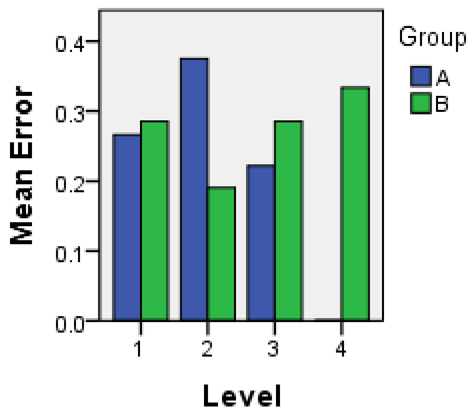


Chart 5.21: Error rate mean per level using the Emotiv

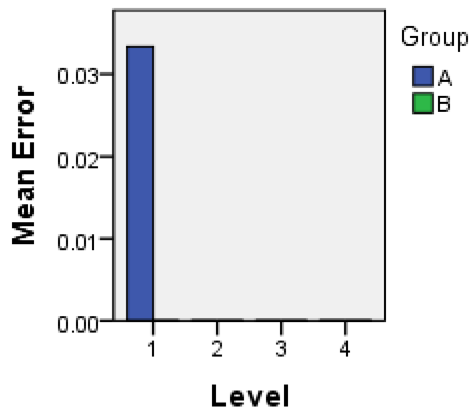


Chart 5.22: Error rate mean per level using the keyboard

Considering the factor usability test (Table 5.8), there was no significant difference between the sequential usability tests for both groups for levels 1 (Chart 5.15), 2 (Chart 5.16), 4 (Chart 5.18) and 6, with the exception of level 3 (Chart 5.17). Chart 5.17 indicates that the variance detected was from the higher error rate during the second test, compared to the other usability tests for both groups. Since an improvement in performance would appear as a negative trend in the graph, this indicates that there is no evidence of improvement for level 3. As usability tests were not significant for the other levels it can be said that there was no significant improvement in performance across the levels.

Similar to efficiency, the usability test factor did not return significance for level 6 (Table 5.8), but the graphs were analysed for interest's sake. Unlike efficiency, the level 6 usability tests for effectiveness gave disparate results for both the Emotiv and keyboard (Table 5.8). While the efficiency results were similar, the effectiveness results for both the Emotiv (Chart 5.19) and keyboard (Chart 5.20) for level 6 appeared different. Using both input methods Group A and B performed similarly for usability tests 1 and 3. However, both groups performed unusually with the two input methods for the second usability test. With the Emotiv group A performed the best while Group B performed the worst. With the keyboard, both groups made errors, with Group B doing noticeably worse. The problem may be complacency: the participants found the first usability test relatively easy to accomplish. The groups became complacent and both groups then underperformed during the second usability test. Their performance then improved during the third usability test when they realised they were making errors.

Considering a broader graph for all the levels (Chart 5.21 and Chart 5.22), it was clear that the keyboard outperformed the Emotiv in effectiveness by a wide margin. It was also of interest that in Chart 5.21 the level 2 result, *move backwards*, was Group A's worst performance and Group B's best. From this point onwards, Group A improved, while Group B got steadily worse. Again, it was possible that Group B's best practices schema was violated. As discussed previously, according to cognitive theory, if a new interface was not congruent to the pre-existing schema it can cause disorientation for the participant, resulting in computer anxiety and reduced performance (Chalmers, 2003). Group B struggled to develop a working schema, which affected their effectiveness performance. This could also have caused frustration for the participants, further degrading their performance. These results were evidenced in the two groups' performance with efficiency as well.

Considering all the evidence, we can therefore reject the null hypothesis $H_{0,3}$ and repetitive use of the Emotiv has no effect on the errors made for an action when using a Emotiv.

5.5 Participant Satisfaction

The participants who completed the study completed a post-test questionnaire, which provided a general view of how the participants felt about the Emotiv system. The responses indicated the participants' overall reaction to the system, their opinions regarding how difficult it was to learn to use the Emotiv, how capable the Emotiv was to use and in what context the Emotiv was acceptable to use. For interest's sake, the discussion will conclude with descriptions of some of the imagery used by the participants as a control signal (Section 5.6).

Of the 18 participants who completed the study from both groups, 13 completed the questionnaire. The remaining five respondents did not complete the questionnaire in its entirety and their results had to be discarded. A Chi-square analysis was administered on the satisfaction results, but it was determined that the results were unreliable. According to (Campbell, 2007) a Chi-squared test should have an expected value of at least one and the results from the analysis of the questionnaire all reported expected values of less than one. Thus, the results captured from both groups were placed in frequency tables and inspected.

5.5.1 Satisfaction Analysis

The frequency Table 5.9 displays the general reaction to the Emotiv as an input method. The results for question 1 indicate that Group A felt neutral about the system, while Group B felt positive about its use. Both groups felt indifferent about whether the system was difficult or easy to use (Question 2). Based on the fact that all participants for group A answered positively when asked how satisfying the system is to use (Question 3), one can say that Group A did not find the Emotiv system particularly frustrating to use, while Group B generally found the system satisfying to use (4 positive responses, 2 negative). The responses for question 4 were all positive and indicate that both groups felt the Emotiv was stimulating to use. The final question results for this section (Question 5) had a disparity between the two groups, Group B (μ=4.14) felt the system was relatively flexible, while Group A (μ=3.17) gave a mixed response.

Table 5.9: Participants overall reaction to the Emotiv

				Distribution of Responses				
				1	2	3	4	5
Group	Item	N	Mean	N (%)	N (%)	N (%)	N (%)	N (%)
OVERALL REACTION TO THE EMOTIV SYSTEM								
A	1.terrible...wonderful	6	3.83	0 (0)	1 (16.7)	1 (16.7)	2 (33.3)	2 (33.3)
B		7	4.43	0 (0)	0 (0)	0 (0)	4 (57.1)	3 (42.9)
A	2.difficult...easy	6	2.83	0 (0)	2 (33.3)	3 (50.0)	4 (16.7)	0 (0)
B		7	3.00	0 (0)	1 (14.3)	5 (71.4)	1 (14.3)	0 (0)
A	3.frustrating... satisfying	6	3.00	0 (0)	2 (33.3)	3 (50.0)	0 (0)	1 (16.7)
B		7	3.71	0 (0)	0 (0)	3 (42.9)	3 (42.9)	1 (14.3)
A	4.dull...stimulating	6	4.33	0 (0)	0 (0)	0 (0)	4 (66.7)	2 (33.3)
B		7	4.57	0 (0)	0 (0)	0 (0)	3 (42.9)	4 (57.1)
A	5.rigid...flexible	6	3.17	0 (0)	0 (0)	3 (50.0)	2 (33.3)	1 (16.7)
B		7	4.14	0 (0)	0 (0)	1 (14.3)	4 (57.1)	2 (28.6)

Overall, it appears that Group B had a more positive outlook towards the system. However, Group A did not respond negatively – they gave neutral responses. There was also no difference detected for efficiency or effectiveness between Group A and B when using the Emotiv to navigate small robots. Thus, comparing the experience that the users had between the two groups should yield similar results. This supports the subjective findings that the participant's reaction to the system was favourable.

Table 5.10: Participants' opinions regarding learning to use the Emotiv

				Distribution of Responses				
				1	2	3	4	5
Group	Item	N	Mean	N (%)	N (%)	N (%)	N (%)	N (%)
LEARNING								
A	1.Learning to operate the system: difficult. easy	6	3.67	0 (0)	2 (33.3)	1 (16.7)	0 (0)	3 (50.0)
B		7	4.00	0 (0)	0 (0)	3 (42.9)	1 (14.3)	3 (42.9)
A	2.Tasks can be performed in a straight-forward manner: never. always	6	2.83	0 (0)	2 (33.3)	3 (50.0)	1 (16.7)	0 (0)
B		7	3.86	0 (0)	0 (0)	3 (42.9)	2 (28.6)	2 (28.6)
A	3.Time to learn to use system: slow. fast	6	3.33	1 (16.7)	0 (0)	2 (33.3)	2 (33.3)	1 (16.7)
B		7	3.57	0 (0)	2 (28.6)	1 (14.3)	2 (28.6)	2 (28.6)

Frequency Table 5.10 contains the results of the questionnaire that measured how easy participants felt the Emotiv system was to learn to use. According to the question 1 results (Group A μ=3.67, Group B μ=4.0), both groups felt that the Emotiv was relatively easy to learn to operate. However, a disparity existed for the results of question 2. Group A (μ=2.83) felt that tasks were not straightforward to complete while Group B (μ=3.86) felt completing tasks with the Emotiv was relatively straightforward. Question 3 indicated that both groups felt that they could master the system relatively quickly (Group A μ=3.33, Group B μ=3.57). This outcome is not supported by the recorded results for effectiveness and efficiency. However, this result could be explained by Tractinsky, Katz and Ikar (2000) who proved that if a system is perceived to be attractive it is also perceived to be more usable. Considering the evidence, it appears that the participants felt that learning to use the system was not difficult.

The section of the questionnaire that measured how capable the participants felt the Emotiv system was to navigate a robot is displayed in the frequency Table 5.11. According to question 1, both groups felt indifferent about the speed and the reliability of the system (Group A μ=3.17, Group B μ=3.43). Both groups also gave neutral responses for the systems reliability according to question 2 (Group A μ=3.00, Group B μ=3.29). Question 3 indicated that Group A (μ=2.17) felt it was moderately difficult to correct a mistake with the system, while Group B (μ=3.14) responded neutrally. Question 4 gave an indication of the physical comfort of the Emotiv, Group A (μ=3.33) felt neutral about the comfort of the headset, while Group B (μ=4.29) found it comfortable.

Table 5.11: Participants feelings on the capability of the Emotiv

				Distribution of Responses				
				1	2	3	4	5
Group	Item	N	Mean	N (%)	N (%)	N (%)	N (%)	N (%)
SYSTEM CAPABILITIES								
A	1.System speed: too slow...fast enough	6	3.17	0 (0)	1 (16.7)	3 (50.0)	2 (33.3)	0 (0)
B		7	3.43	0 (0)	1 (14.3)	4 (57.1)	0 (0)	2 (28.6)
A	2.System reliability: unreliable...reliable	6	3.00	1 (16.7)	1 (16.7)	2 (33.3)	1 (16.7)	1 (16.7)
B		7	3.29	1 (14.3)	1 (14.3)	1 (14.3)	3 (42.9)	1 (14.3)
A	3.Correcting your mistakes: difficult...easy	6	2.17	0 (0)	5 (83.3)	1 (16.7)	0 (0)	0 (0)
B		7	3.14	0 (0)	3 (42.9)	2 (28.6)	0 (0)	2 (28.6)
A	4.Comfort of wearing headset: uncomfortable... comfortable	6	3.33	0 (0)	2 (33.3)	1 (16.7)	2 (33.3)	1 (16.7)
B		7	4.29	0 (0)	1 (14.3)	0 (0)	2 (28.6)	4 (57.1)

Referring to the response to question 3 above, Group A participants responded that it was challenging to correct a mistake with the Emotiv. This result is supported by the observed quantitative results (Section 5.4) where it was clear that participants struggled to recover from an error made with the Emotiv. A possible explanation is that the participants had trouble in switching between actions to correct mistakes. This could have caused a feeling of frustration for the participant, which would increase the difficulty when manoeuvring the robot. The result for question 4 reported that the groups found the headset to be comfortable; this was unexpected, as the device fits tightly around a person's head and requires that the contact points are kept damp with a saline solution.

The next section of the questionnaire measured how acceptable the participants felt the context was in which the Emotiv could be used for navigation (Table 5.12). Examples were chosen for the questions representative of systems that could be used with a BCI for navigation. Question 1's feedback indicated that both groups (Group A μ=3.50, Group B μ=3.43) felt the Emotiv was acceptable to use to control a robot. Likewise, the results from question 2 indicated that both groups (Group A μ=2.67, Group B μ=3.29) felt that the Emotiv would be somewhat acceptable to use to control a motorised wheelchair.

Table 5.12: Participants reactions to the acceptability of the Emotiv for navigation

				Distribution of Responses				
				1	2	3	4	5
Group	Item	N	Mean	N (%)	N (%)	N (%)	N (%)	N (%)
SYSTEM ACCEPTABILITY								
A	Used to control a Mindstorm NXT robot: unreliable...reliable	6	3.50	1 (16.7)	2 (33.3)	1 (16.7)	2 (33.3)	0 (0)
B		7	3.43	1 (14.3)	1 (14.3)	1 (14.3)	2 (28.6)	2 (28.6)
A	Used to control a motorized wheelchair: unreliable... reliable	6	2.67	1 (16.7)	2 (33.3)	1 (16.7)	2 (33.3)	0 (0)
B		7	3.29	1 (14.3)	1 (14.3)	2 (28.6)	1 (14.3)	2 (28.6)
A	Used to control an automated house: unreliable... reliable	6	1.50	4 (66.7)	1 (16.7)	1 (16.7)	0 (0)	0 (0)
B		7	1.71	2 (28.6)	5 (71.4)	0 (0)	0 (0)	0 (0)
A	Used to control a motor vehicle: unreliable... reliable	6	1.67	4 (66.7)	1 (16.7)	0 (0)	1 (16.7)	0 (0)
B		7	1.29	5 (71.4)	2 (28.6)	0 (0)	0 (0)	0 (0)
A	Used to control an aeroplane: unreliable... reliable	6	1.17	5 (83.3)	1 (16.7)	0 (0)	0 (0)	0 (0)
B		7	1.29	5 (71.4)	2 (28.6)	0 (0)	0 (0)	0 (0)

However, the results from both groups indicated that they felt the Emotiv would be unacceptable to use to control a house (Group A μ=1.5, Group B μ=1.71) a motor vehicle (Group A μ=1.67, Group B μ=1.29) and strongly unacceptable for use to control an aeroplane (Group A μ=1.17, Group B μ=1.29).

Considering these subjective results, it appears from the responses that as the complexity of the task and safety issues increased, the acceptability of the system decreased for the participants. This conclusion is further supported by the efficiency and effectiveness results from Sections 5.4 and 5.5. The weak performance of the Emotiv compared to a keyboard would have influenced participant's opinions heavily towards the context in which the Emotiv would be acceptable to use.

5.5.2 Questionnaire Summary

Overall, the participants had positive opinions regarding the use of the Emotiv and felt that it was relatively easy to learn to use the input method. However, the difficulty in correcting errors made the participants feel that using the Emotiv for navigation was difficult. This probably affected the participants' opinions as to what they would consider acceptable as a navigation object to use with the Emotiv, in this case only small robots and motorised wheelchairs. The subjective responses from the participants indicate that they clearly enjoyed using the device and felt the technology had potential.

5.6 Imagined Movement

The participants were asked to write a short description of the imagery they used for each movement as part of the post-test questionnaire given at the end of the study. For interest's sake, this imagery was analysed by assigning the description for the worst result and the best result for each action into a table, which was then analysed (Table 5.13).

The result from imagining a forward movement was particularly interesting. The worst result was a person driving a car, while the best result was imagery involving rotating the Earth. It is likely that the rotating earth imagery was effective because it was visual and easy to imagine compared to the car imagery. However, later in the study when it became necessary to rotate the robots this participant's performance became worse, probably because it caused confusion with the *rotate left* command.

Table 5.13: Examples of imagery used for each action

Action	Worst Result	Best Result
Forwards	I thought about driving in a very fast car.	The rotation of the Earth on its axis, observed from space.
Backwards	A man moving backward on the slope	I think about inhaling air.
Turn Left	A colourless triangle in my mind's eye. Nothing else	Pulling an object (box) with my left hand, in the left direction
Turn Right	Clock-wise movement	Driving in a circle in a clockwise direction

With the *move backwards* command the worst performer was surprising. It was a man walking backwards, which initially would appear to be directly related to the action. Perhaps because the user had imagined another person walking backwards instead of himself, the imagery was not effective. The best imagery had the participant imagine inhaling air, which was easy to replicate and directly related to the action.

The worst imagery for *turn left* was imagining a colourless triangle, an unusual choice. With no direct association with the movement, it was likely too difficult to replicate. The best imagery involved pulling a box to the left. This imagery appears to be related to the desired outcome and relatively easy to replicate.

The best and worst imageries for turning right both involved imagining movement in a clockwise direction. However, the worst result was described abstractly, unlike the driving example, which was a more concrete example. It is possible that “clock-wise movement” is too abstract to replicate easily and resulted in the poor performance.

Considering the analysis it appears that the trend was that the closer the imagery was to the action and the simpler the imagery, the better the command was performed.

5.7 Discussion

For the participants of this study the keyboard clearly outperformed the Emotiv as an input method. The results from the study, once analysed, reported that the keyboard was less error prone and took less time when completing a navigation task.

The satisfaction measurements indicated that the participants felt that the Emotiv was relatively easy to learn to use. They also felt that the Emotiv was fairly responsive and comfortable to wear. The major disadvantage reported by the participants was that they found it difficult to correct mistakes made with the Emotiv. This could be because participants had difficulty trying to switch to the required opposite action quickly. As participants made more errors with the Emotiv compared to the keyboard, this presented a problem with the usability of the Emotiv and was an obstacle to the device's acceptability as an input method. However, generally, the participants were excited to use the headset and they would use it again if given the opportunity.

The results from the repeated measures ANOVAs for this study also demonstrated that there was no difference between Group A and Group B when using the Emotiv to navigate small robots. For both efficiency and effectiveness, the group to which a participant belonged to was found to have no significant effect on the usability measures. Since the groups were classified based on exposure to technology this indicated that a participant's access to traditional input methods had no significant effect on their performance with the Emotiv. This was an encouraging result, as knowledge of computers is then not a requirement for the input method, which broadens the applicability of the Emotiv as an alternative to the traditional approach of a keyboard.

The results revealed that repetitive use in the short term caused no improvement in performance with the Emotiv when used to control a robot. These results were disappointing, but are not representative of learning as a better measurement of learnability would be a longitudinal study conducted over a long period of time – a goal outside the scope of this study, but planned for future work.

In conclusion, the users did not significantly improve between successive usability tests. No significant difference between the performances of the Emotiv for the two groups was found. However, there was a significant difference in performance between using the keyboard or Emotiv to complete a task. The keyboard proved to be a superior input method, but all the participants had some previous experience with the keyboard, which may explain the improved performance. None of the participants had experience with an EEG BCI; yet, with minimal training, they were able to utilise the Emotiv to navigate the robot through a test course, which is encouraging. As exposure to input methods was not a factor affecting a participant's performance, the BCI has the advantage of being accessible. This accessibility could be a valuable attribute for an input method as part of a NUI. However, the results indicated that with the Emotiv it was difficult to correct errors and the subjective responses indicated that it would not be acceptable to control a device more complicated than a motorised wheelchair. As such, EEG BCIs still need to be developed further before they can be used as the primary input method for navigation. However, it has potential as an accessible input method for users.

5.8 Summary

This chapter analysed and then discussed the data captured from the usability measures *efficiency, effectiveness, learnability* and *satisfaction*. Two groups of participants were classified based on their exposure to traditional input methods and then compared using various usability metrics. In the short term, no learning was evident with the Emotiv. However, there was a significant difference between navigating the robot using the Emotiv compared to a keyboard and it was discovered that exposure to traditional input methods had no significant impact on a participant's performance with the Emotiv. Subjectively, the participants had positive opinions regarding the use of the Emotiv and they felt that it was relatively easy to learn to use. However, participants reported that correcting errors with the Emotiv was difficult.

The next chapter will draw conclusions based on the analysed data and discuss possible future work.

Chapter 6: Conclusion

6.1 Introduction

The main aim of this study was to investigate the usability of a BCI for robot navigation (Chapter 1). To achieve this, two groups, which were classified by their exposure to traditional input methods, were compared, based on the usability metrics *learnability*, *efficiency, effectiveness* and *satisfaction* (Chapter 4). The previous chapter (Chapter 5) analysed and discussed these metrics, which were captured while participants navigated the robot through a course, as well as the subjective results obtained from the post-test questionnaire.

This chapter will answer the research questions and hypotheses posed in the introduction (Chapter 1), based on the results of the analysis. The study's findings will be discussed and the contribution made to the field will be highlighted. The final section will provide recommendations followed by possibilities for further research.

6.2 Motivation

Traditional input methods are being replaced or supplemented by natural modes of interaction to allow for interfaces that are more intuitive and thus easier to learn for a user. The results from this study gave insight into the usability of a BCI and an indication of the Emotiv's suitability as a NUI.

It was previously established that the majority of BCI research provided communication and control to persons with disabilities. This has resulted in a shortage of available research on the application of a BCI for able users. This study contributed by examining whether a user's previous experiences with a traditional input method, such as a keyboard, would influence the usability of a BCI like the Emotiv.

6.3 Study Findings

Previously, three research questions (Chapter 1) were formulated based on the problem statement for this study. These questions will each be considered and answered; in turn, based on the analyses from the previous chapter (Chapter 5).

The questions will be answered based on the usability metrics *effectiveness, efficiency* and *satisfaction*. Effectiveness and efficiency measures were captured while navigating a robot through a test course using five predefined actions. Using repeated measures ANOVAs, these usability metrics were analysed, while satisfaction was captured via a post-test questionnaire.

Does a user's exposure to traditional input methods influence a user's performance with a BCI when navigating a robot?

In order to answer this question, it had to be determined whether there was a significant difference between the two groups in terms of the usability metrics effectiveness, which was defined as the number of errors made, or efficiency, as the time required to complete a task. The results from the usability tests detected no significant difference between the groups' efficiency and effectiveness when using the Emotiv to complete a task. Thus, a user's previous experience with a traditional input method does not influence a user's performance with an Emotiv when navigating a robot. The first hypothesis, namely that exposure to a traditional input method does not influence a user's performance when manoeuvring a robot using a BCI, was thus not rejected.

Therefore, no prior knowledge of how to use a computer and its traditional input methods is required in order to interact with a system. This result is promising, as it indicates that the Emotiv is an intuitive interface. As the interface is intuitive, the Emotiv could be a suitable candidate for use with a NUI.

Does the user's performance with a traditional input method differ from a BCI when navigating a robot?

Two input methods were tested during the course of this study: the Emotiv and a keyboard. Both input methods were used for each usability test so that the results could be compared. The results for the usability metrics efficiency and effectiveness indicated that there was a significant difference between the performances with the Emotiv and a keyboard. For every task, the keyboard outperformed the Emotiv. Therefore, a user's performance with a traditional input method differs from the Emotiv when navigating a robot. Thus, the hypothesis that there is no difference in a user's performance when using a traditional input method compared to using a BCI when manoeuvring a robot was rejected.

The results indicated that the participants made more errors and took more time to complete a task with the Emotiv, compared to the keyboard. These results could be explained according to the cognitive theory that a schema is created based on how an interface is expected to work. The violation of this preformed schema could cause reduced performance. Since all the participants had previous experience utilising the keyboard, but were first-time users of the Emotiv, they could have tried to apply their previous experiences with a keyboard when controlling the Emotiv. Another factor that influenced performance for Group B was complacency, which was observed when the participants were tested on the first test course (Appendix C). The participants did well on the first usability test and then poorly on the second, recovering for the third test. As this was the high-exposure group, this suggests that because of their previous experience, they quickly became comfortable with Emotiv, thus losing concentration on the task, which affected their performance negatively. However, because participants quickly became comfortable using the Emotiv, this supports the evidence that the headset is an intuitive interface. The participants learned to utilise the Emotiv quickly and felt that it was enjoyable to use. Therefore, the application of the Emotiv as a NUI is still viable.

Does repetitive use of a BCI to navigate a robot improve a user's performance?

Each usability test was repeated three times per action to measure whether there was a short-term improvement in performance (Chapter 3), but with neither the usability metrics efficiency nor effectiveness was a significant improvement detected. Thus, repetitive use of the Emotiv to navigate a robot does not improve a user's performance and the hypothesis that repetitive use of a BCI has no effect on user performance when using a BCI could not be rejected.

The results in this study are only representative of learning over a short period. Subjectively, the participants reported that the Emotiv was not difficult to learn to use, despite the data collected. This result can be explained, because a system that is considered attractive is then perceived by users to be usable. As has been established, the Emotiv is intuitive and comfortable for participants to use. This should improve the learning pace for users of the interface. A longer study period could reveal improved performance.

In summary, there was no difference between the usability of the Emotiv based on prior exposure to input methods and the repetitive usability tests had no significant impact on a participant's performance. The participants did feel that the Emotiv was enjoyable to use and has potential as an input method. While the Emotiv was not as efficient or effective as the keyboard, it was found to be intuitive and usable. These results compare favourably with the results from Vourvopoulos and Liarokapis (2012) who, in a qualitative study, reported positive responses when using the Emotiv with imagined movement to navigate a robot.

6.4 Contribution to the field

This research investigated whether a BCI's usability is influenced by a user's exposure to traditional input methods and proposed utilising a BCI as an alternative input method, such as a NUI. Towards this end, it was determined that there was a significant difference between the performance of a keyboard and the Emotiv and that short-term repetitive use of a BCI does not improve a participant's performance. These results indicate that in terms of efficiency and effectiveness the keyboard is the superior interface. However, it was found that exposure to traditional input methods did not affect an able participant's performance when utilising a BCI. Therefore, the Emotiv was found to be intuitive to use and appears suitable for use as a NUI.

This study proved that the Emotiv is an intuitive interface and is usable with little to no previous experience required. This study identified various shortcomings of the Emotiv, if these disadvantages are overcome then this study can be used as a foundation on which to base a study on the use of the Emotiv as a NUI.

6.5 Recommendations

The Emotiv was found to be capable but not as efficient or effective as a keyboard. The headset took longer to complete a task and was more error prone than the keyboard. The difficulty in correcting navigation errors lowered the acceptability of the Emotiv. The participants indicated that the context in which the Emotiv would be acceptable to use should not be more complicated than a motorised wheelchair. As such, the Emotiv should not be used for critical tasks such as navigating a motor vehicle.

The Emotiv has been shown to be intuitive, but with limited applicability. The Emotiv's API can only use four commands at any one time; thus, abstract commands should be used to maximise the ability of the headset. A context should be chosen that is not time sensitive and can make use of abstract commands such as *move to another room*.

The responsiveness of the robot to a command given by a participant was such that any delay was not noticeable with the Emotiv. Furthermore, as the headset is a wireless device it is ideal as a mobile hands-free interface.

Although not an aim of this research, it was discovered during analysis that there is a trend that, the closer the imagery was to the action and the simpler the imagery, the better the command appeared to perform. These findings should be applied in further studies or in general use of the BCI when using imagery for commands, as they are more effective.

The recommendation for the Emotiv as a control interface is to use the headset in a limited capacity. The device could be combined with another input method for the aspects of the task that require finite control, if the user is capable of performing such an action, or the commands required from the Emotiv should be abstracted.

6.6 Further Research

The results of this study point to a number of options for further research. Firstly, there is a need to measure the effects of learning accurately and definitively by using a longitudinal study on a commercial BCI similar to the Emotiv. Secondly, a study is required with a diverse sample of users that can be compared on their exposure to traditional input methods in order to confirm the results of this research. This study utilised university students, therefore extending the study to include able users from the public will have value. Thirdly, this study utilised imagery as the command signals with the Emotiv. It should be investigated whether simple imagery that is based on the intended action would be more efficient. A number of BCI techniques are also available to use as was discussed in Chapter 2. A comparison between these different BCI techniques and this study could have value. Fourthly, the Emotiv could be compared to other similar BCIs in order to test how viable those interfaces would be for navigation. Fifthly, the Emotiv is a wireless device and has the capability to be a mobile interface. This capability should be investigated thoroughly. Lastly, the results indicated that the Emotiv is intuitive and has potential as a NUI. The headset could be combined with another interface that can make up for the Emotiv's weaknesses to create a robust NUI. This potential should be investigated thoroughly in different contexts.

6.7 Summary

Traditionally, research that involved BCIs has focused on enabling persons with disabilities to communicate or move by using prosthesis. These systems typically assisted relatively few individuals in a controlled environment and often required a team of researchers to operate. Globally, recent trends with BCI research have started to research the use of a BCI as an alternative or supplementary interface. Despite this trend, there was still a shortage of research available regarding the utilisation of BCIs and able users.

To address this shortfall, the Emotiv was utilised with able users for this study to discover whether exposure to traditional input methods affected the usability of a BCI.

The study discovered that previous experience with traditional input methods is not a requirement to use the Emotiv. Furthermore, although the keyboard outperformed the Emotiv, the participants quickly became comfortable with using the headset and described the interface as easy to learn and enjoyable to use. These results indicate that the Emotiv is an intuitive interface to use. Thus, the Emotiv is a powerful intuitive interface that has potential as or as part of a NUI.

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Appendix A

Sign-up Questionnaire

1. Full name and surname: ____

2. Student number: ____

3. E-mail address: ____

4. Home address: ____

   ____

   ____

5. Contact Number: ____

6. Age: __________

7. Gender(M/F): __________

8. Highest qualification attained: ______________________________

9. Through which faculty are/were you pursuing your degree: ______________________________

10. Which campus are you a student with?

    [ ] Bloemfontein Campus [ ] Qwaqwa Campus [ ] Vista Campus

11. For how long have you been using computers?

    [ ] Never [ ] 1 - 3 Months [ ] 3 - 6 months
    [ ] 6 months - 1 year [ ] 1 year - 2 years [ ] 2 years - 3 years
    [ ] 3 years - 5 years [ ] 5 years - 10 years [ ] more than 10 years

12. If you did not answer **Never** in question 11; How many times a week do you use a computer?

    [ ] Once a week [ ] Twice a week [ ] Three times a week [ ] Four times a week [ ] Five times a week [ ] Daily [ ] Multiple times a day

13. If you did not answer **Never** in question 11; What types of programs do you use on a computer?

    [ ] Word Processing [ ] Spreadsheet [ ] E-mail [ ] Internet Surfing [ ] Games [ ] Programming [ ] Multimedia

    [ ] Other:____

Questionnaire for Computer Anxiety

Please circle your chosen response

Key:

1=Strongly disagree, 2=Disagree, 3=Mildly disagree, 4=Mildly agree, 5=Agree, 6=Strongly agree

I feel anxious when …	SD	D	MD	MA	A	SA
1. ... thinking about taking a class in a programming language (e.g. Basic, Pascal, C++, etc).	1	2	3	4	5	6
2. … applying for a job that requires some training in computers.	1	2	3	4	5	6
3. … sitting in front of a home computer.	1	2	3	4	5	6
4. ... being around people who are “into” computers.	1	2	3	4	5	6
5. … watching a movie about an intelligent computer.	1	2	3	4	5	6
6. … looking at a computer print-out.	1	2	3	4	5	6
7. … getting error messages from the computer.	1	2	3	4	5	6
8. … watching or listening to news programs about the increasing role of computers in society.	1	2	3	4	5	6
9. … watching someone working at a computer terminal.	1	2	3	4	5	6
10. … being refused information because a terminal is “down”.	1	2	3	4	5	6
11. ... talking to a computer programmer.	1	2	3	4	5	6
12. … learning to write computer programmes.	1	2	3	4	5	6
13. … using a typewriter.	1	2	3	4	5	6
14. … visiting a computer shop.	1	2	3	4	5	6
15. ... attending a workshop on the uses of computers.	1	2	3	4	5	6
16. ... erasing or deleting material from a computer.	1	2	3	4	5	6
17. … thinking about programmes for computers.	1	2	3	4	5	6
18. … taking a class about the uses of computers.	1	2	3	4	5	6
19. … learning computer technology.	1	2	3	4	5	6
20. … looking at a high speed computer printer.	1	2	3	4	5	6

Thank you for applying to participate in this study

Appendix B

Emotiv EPOC Usability Questionnaire

1. Describe what you think about when you move the robot FORWARD using the Emotiv EPOC headset.

Describe what you think about when you move the robot FORWARD using the Emotiv EPOC headset.

2. Describe what you think about when you move the robot BACKWARD using the Emotiv EPOC headset.

Describe what you think about when you move the robot BACKWARD using the Emotiv EPOC headset.

3. Describe what you think about when you try to get the robot to TURN LEFT using the Emotiv EPOC headset.

Describe what you think about when you try to get the robot to TURN LEFT using the Emotiv EPOC headset.

4. Describe what you think about when you try to get the robot to TURN RIGHT using the Emotiv EPOC headset.

Describe what you think about when you try to get the robot to TURN RIGHT using the Emotiv EPOC headset.

5. Describe what you think about when you switch between the robots AMBER and BLOO using the Emotiv EPOC headset.

Describe what you think about when you switch between the robots AMBER and BLOO using the Emotiv EPOC headset.

6. OVERALL REACTION TO THE SYSTEM

	1	2	3	4	5	N/A
terrible...wonderful	☐	☐	☐	☐	☐	☐
difficult...easy	☐	☐	☐	☐	☐	☐
frustrating...satisfying	☐	☐	☐	☐	☐	☐
dull...stimulating	☐	☐	☐	☐	☐	☐
rigid...flexible	☐	☐	☐	☐	☐	☐

7. LEARNING

	1	2	3	4	5	N/A
Learning to operate the system: difficult...easy	☐	☐	☐	☐	☐	☐
Tasks can be performed in a straight-forward manner: never...always	☐	☐	☐	☐	☐	☐
Navigating Course A using keyboard: difficult...easy	☐	☐	☐	☐	☐	☐
Navigating Course A using Emotiv EPOC headset: difficult...easy	☐	☐	☐	☐	☐	☐
Navigating Course B using keyboard: difficult...easy	☐	☐	☐	☐	☐	☐
Navigating Course B using Emotiv EPOC headset: difficult...easy	☐	☐	☐	☐	☐	☐
Time to learn to use system: slow...fast	☐	☐	☐	☐	☐	☐

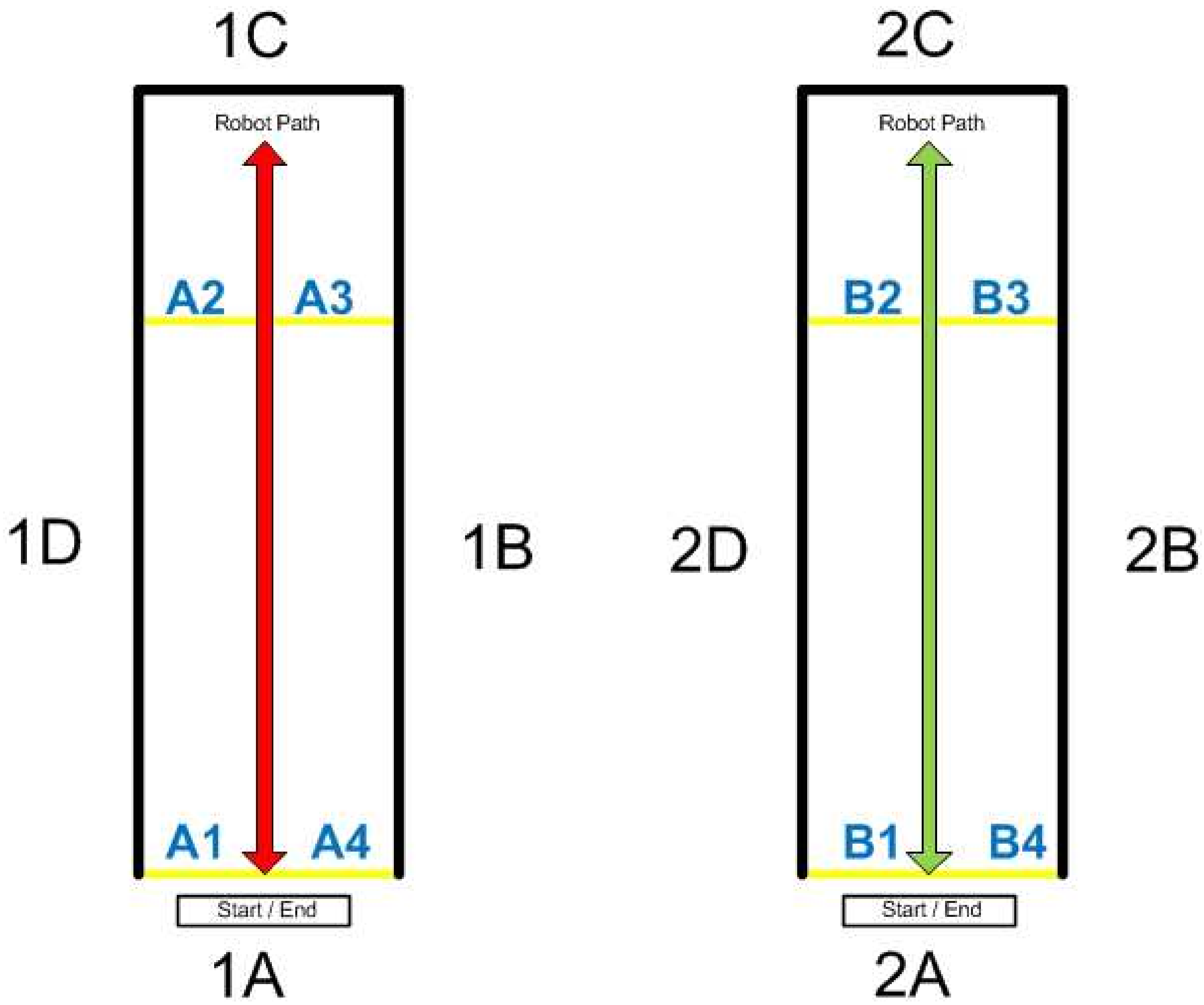
8. SYSTEM CAPABILITIES

	1	2	3	4	5	N/A
System speed: too slow...fast enough	☐	☐	☐	☐	☐	☐
System reliability: unreliable...reliable	☐	☐	☐	☐	☐	☐
Correcting your mistakes: difficult...easy	☐	☐	☐	☐	☐	☐
Comfort of wearing headset: uncomfortable...comfortable	☐	☐	☐	☐	☐	☐

9. SYSTEM ACCEPTABILITY

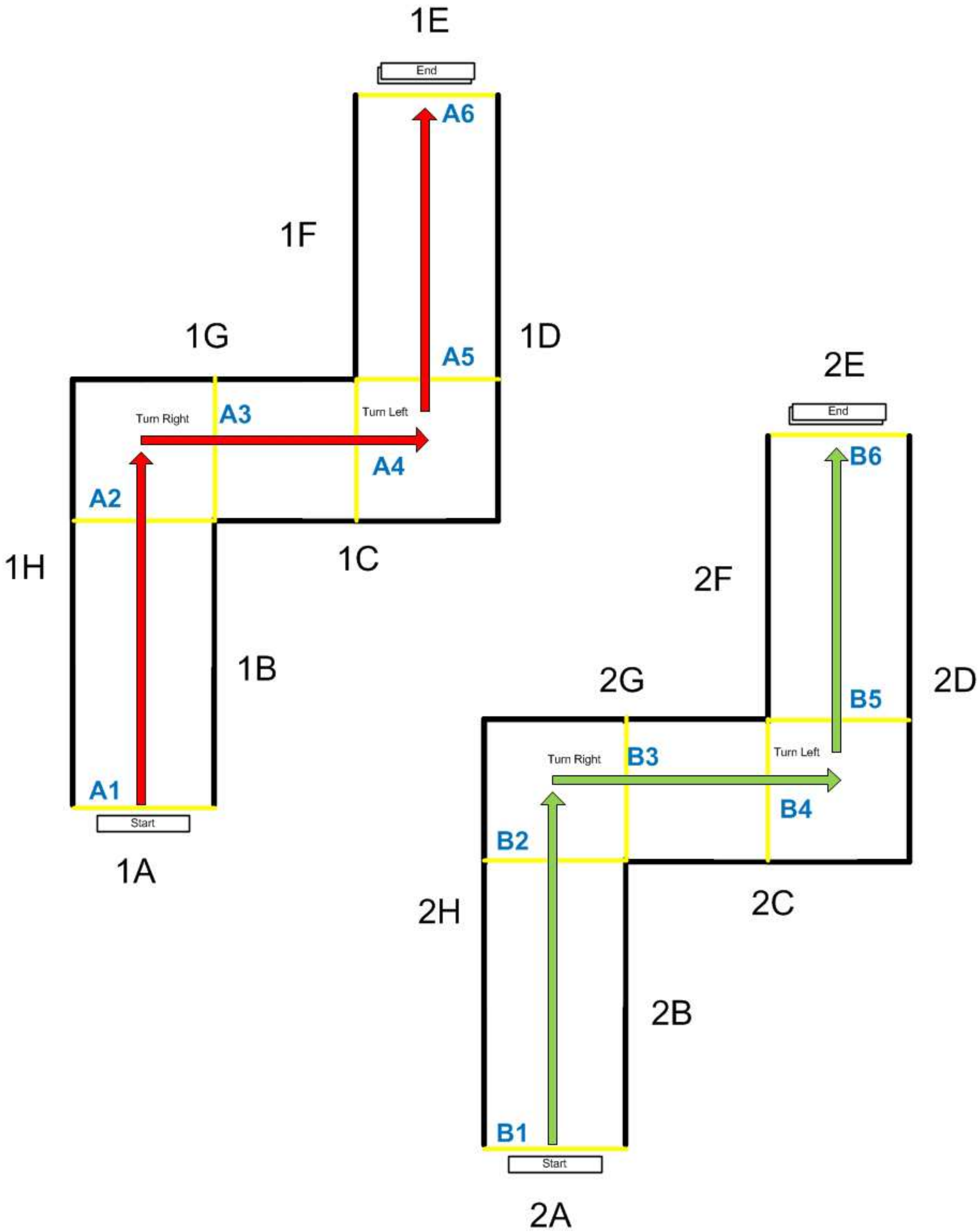
	1	2	3	4	5	N/A
Used to control a Mindstorm NXT robot: unreliable...reliable						
Used to control a motorized wheelchair: unreliable...reliable						
Used to control a automated house: unreliable...reliable						
Used to control a motor vehicle: unreliable...reliable						
Used to control a aeroplane: unreliable...reliable						

Appendix C



1C
Robot Path
A2
A3
1D
1B
A1
A4
Start / End
1A
2C
Robot Path
B2
B3
2D
2B
B1
B4
Start / End
2A

Appendix D


1E
End
A6
1F
1G
1D
A5
Turn Right
A3
Turn Left
A4
A2
1H
1C
1B
A1
Start
1A
2E
End
B6
2F
2G
2D
B5
Turn Right
B3
Turn Left
B4
B2
2H
2C
2B
B1
Start
2A

Appendix E

University of the Free State

Department of Computer Science and Informatics

Exploring the use of Brain-Computer Interfaces for Human-Robotic Interaction

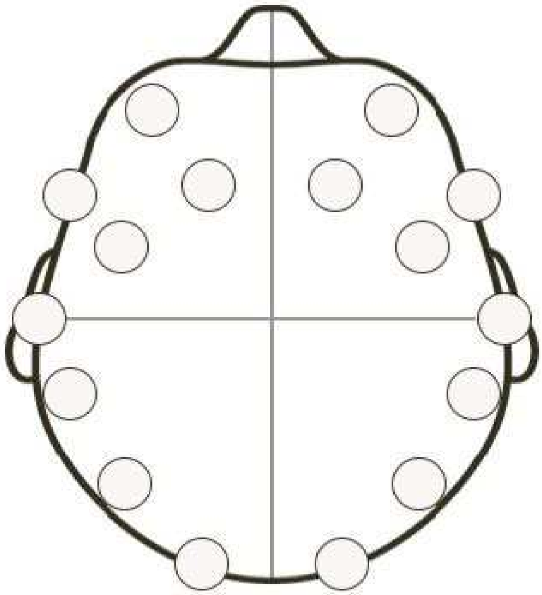
Student Number:_____________________________ Session Number: ___________________

Session Level: ___________________

Before Session Start Checklist

Switch cellphone off	
Alpha Robot is charged	
Beta Robot is charged	
Emotiv EPOC headset is charged	
Obstacle course is setup and ready	
Robot Alpha connects via bluetooth	
Robot Beta connects via bluetooth	
Emotiv EPOC headset connects via Bluetooth	
Setup Emotiv EPOC headset using Control Panel on user and ensure connection points are green	
Application connects to database	
Setup user details in supplied fields	
Record session ID	
Ensure room is sealed and that door is closed	

Comments:



**Mark nodes with a poor connection with R = Red or O= Orange.*

Before Trial Session Start Checklist

Session Key	1	2	3	4	5	6
Check robot(s) are in correct starting location for trial.						
Check participant understands what they need to do						
Check robot(s) are on and connected						

SessionID records:

	First Round	Second Round	Third Round
Training SessionID	A	B	C
Keyboard Trial SessionID	1	3	5
Emotiv Trial SessionID	2	4	6

Training session results:

			(Push)	**(Pull)**	**(TurnLeft)**	**(TurnRight)**	**(Lift)**
ID	**Start Time**	**End Time**	**Push %**	**Pull %**	**TurnLeft%**	**TurnRight%**	**Switch%**
A							
B							
C							

Trial session results:

ID	**Start Time**	**End Time**	**Out of Bounds**	**Error Count**	**Ratio**
1					X
2					
3					X
4					
5					X
6					

During Session Guidelines

- Be positive and supportive but do not interfere, let the participant work it through

- Participant has a limited time to complete a course using the keyboard and the Emotiv EPOC headset.
- Participant must be wearing the Emotiv EPOC headset when testing with the keyboard.
- If a participant fails to complete course, record progress made (see Session Progress key) and end the session. Reassure the participant; remind them that everything they do is useful.
- If a robot completely crosses over line and is out of bounds, offer to move robot back on course to where it crossed over the line.
- During training, if a participant appears particularly frustrated and is struggling, let them take a minute break.
- In-between sessions the application will need to save data, during this time distract the participant and give them a chance to rest; subjects must not remove the headset.
- If connection to headset is lost, reset connection and continue. Ensure that the anomaly is logged on the session sheet.
- If application crashes/freezes. Log anomaly and reset session.
- If participant exceeds training time without achieving the necessary skill rating, move onto the task trials. (This occurs after 60 minutes of training, two sessions)

Training Session Guidelines

- When training push and pull actions follow the following procedure
  - The push and pull training sessions must be consecutive.
  - Train actions until participant gets above 50% skill.
  - Allow participant to rest and ask them to reflect on how to apply actions. Have the participant practice the actions in their own mind.
  - Re-train actions until above 50% skill with no feedback from the robot.
  - Run the test cases.

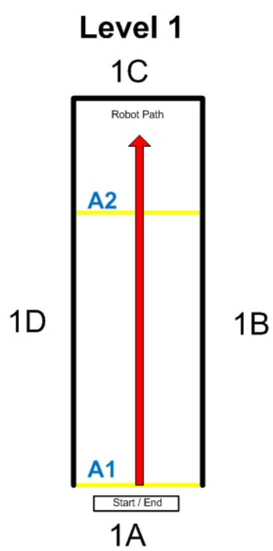
End Session Guidelines

- Count Out of Bound events and write total on session sheet under Error Count.
- Give your opinion on their control ratio.
- Thank participant for their time and effort

Key for Out of Bound events and Session Progress

<u>Out of bound event:</u> Record where robot went out of bounds using key (black number) from map below (example on Course A robot Alpha exists course on the left, mark down the code 1D under column Out of Bounds)

<u>Session Progress:</u> Record robots final progress at the end of session (blue number). If participant completed both courses simply mark session sheet with the code for the course (for Course A = A4/B4, for Course B = A6/B4). However if participant runs out of time mark the progress of the last yellow line they crossed with each robot.



Training Levels

Level 1 :

Push Training - Participant must move robot forwards

Requirements :

- Participant must have a push skill rating in the Emotiv Control Panel of at least 50%
- Participant has a maximum training time of 60 Minutes (2 Sessions)
- Participant must perform three test cases.
- If Participant reaches 50% training or maximum training time, move onto next level.

Push Ratio :

0	1	2	3	4
No Control.	Small, inconsistent movements.	Small, consistent movements.	Good control with occasional problems.	Complete control.

Test Case Description:

[Course A] The user first moves the robot using the keyboard, then using the Emotiv EPOC headset. Participant must move robot forward over the A1 yellow line until the robot crosses the A2 yellow line. When the robot has completely passed over the A2 yellow line the test case is complete. The user has a maximum of 5 minutes to complete this test case.

Test Case Completion Code:

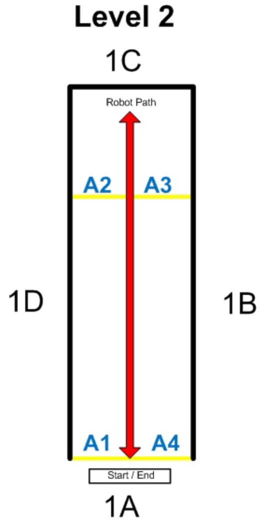
1. Mark session sheet A1 when participant crosses robot over A1 yellow line
2. Mark session sheet A2 when participant crosses robot over A2 yellow line

Level 2 :

Pull Training - Participant must move robot backwards

Requirements :

- Participant must have a pull skill rating in the Emotiv Control Panel of at least 50%
- Participant has a maximum training time of 60 Minutes (2 Sessions)
- Participant must perform three test cases.



- If Participant reaches 50% training or maximum training time, move onto next level.

Pull Ratio :

0	1	2	3	4
No Control.	Small, inconsistent movements.	Small, consistent movements.	Good control with occasional problems.	Complete control.

Test Case Description:

[Course A] The user first moves the robot using the keyboard, then using the Emotiv EPOC headset. The participant must move robot backwards over yellow line A3 until robot crosses over yellow line A4. When the robot has completely passed over the A4 yellow line the test case is complete. The user has a maximum of 10 minutes to complete this test case.

Test Case Completion Code:

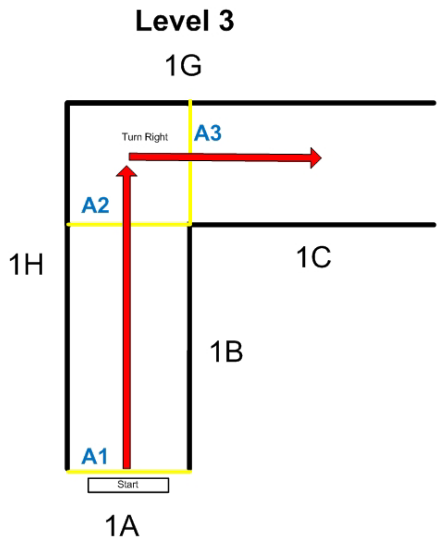
1. Mark session sheet A3 when participant crosses robot over A3 yellow line
2. Mark session sheet A4 when participant crosses robot over A4 yellow line

Level 3 :

Turn Right Training - Participant must turn robot right

Requirements :

- Participant must have a right skill rating in the Emotiv Control Panel of at least 50%
- Participant has a maximum training time of 60 Minutes (2 Sessions)
- Participant must perform three test cases.
- If Participant reaches 50% training or maximum training time, move onto next level.



Turn Right Ratio :

0	1	2	3	4
No Control.	Small, inconsistent movements.	Small, consistent movements.	Good control with occasional problems.	Complete control.

Test Case Description:

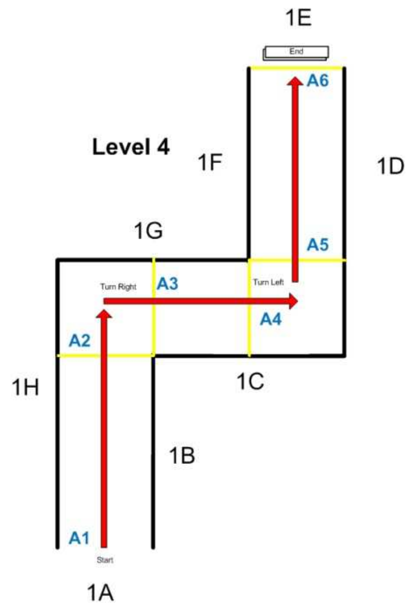
[Course B] The user first moves the robot using the keyboard, then using the Emotiv EPOC headset. The participant must rotate the robot right until the robot faces the A3 yellow line. When the robot faces the A3 yellow line straight on the test is complete. The user has a maximum of 5 minutes to complete this test case.

Test Case Completion Code:

1. Mark session sheet A3 when robot faces A3 yellow line

Level 4 :

Turn Left Training - Participant must turn robot left



Requirements :

- Participant must have a left skill rating in the Emotiv Control Panel of at least 50%
- Participant has a maximum training time of 60 Minutes (2 Sessions)
- Participant must perform three test cases.
- If Participant reaches 50% training or maximum training time, move onto next level.

Turn Left Ratio :

0	1	2	3	4
No Control.	Small, inconsistent movements.	Small, consistent movements.	Good control with occasional problems.	Complete control.

Test Case Description:

[Course B] The user first moves the robot using the keyboard, then using the Emotiv EPOC headset. The particpant must rotate the robot left until the robot faces the A5 yellow line. When the robot faces the A5 yellow line straight on the test is complete. The user has a maximum of 5 minutes to complete this test case.

Test Case Completion Code:

1. Mark session sheet A5 when robot faces A5 yellow line

Level 5 :

Activate Robot Training - Participant will be able to switch control focus between the robots.

Requirements :

- Participant must have a lift skill rating in the Emotiv Control Panel of at least 50%
- Participant has a maximum training time of 60 Minutes (2 Sessions)
- Participant must perform three test cases.
- If Participant reaches 50% training in the lift action or maximum training time, move onto next level.

Activate Ratio :

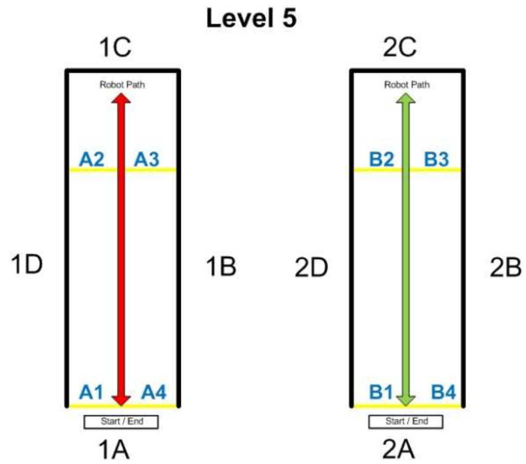
0	1	2	3	4
No Control.	Inconsistent activations.	Participant can activate robot occasionally.	Participant can usually activate robot.	Complete control.

Test Case Description:

[No Course] The user switches control to the other robot (Yellow root to Blue robot) then back again (Blue robot to Yellow robot). Once this is done, the test is complete.

Test Case Completion Code:

1. Mark session sheet A1 when participant crosses robot alpha over A1 yellow line
2. Mark session sheet A when participant activates robot alpha
3. Mark session sheet B when participant activates robot beta



Level 6 :

Requirements :

- Participant must perform three test cases.
- Participant has a maximum time to complete a action, if time passes move robot for participant and move onto next action.

Action Task Timing :

- Participant has a maximum total of 15 minutes to complete the task.

- If the participant is struggling and is making no progress the researcher may end the session after 10 minutes has passed.

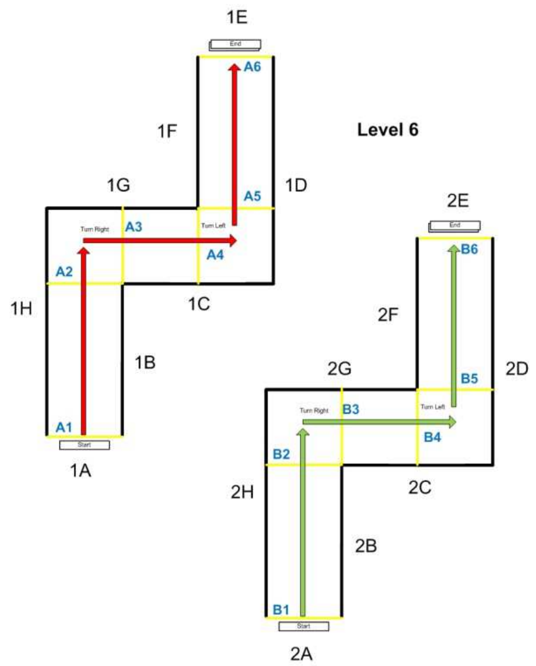
Test Case Description:

[Course A] The user first moves the robots using the keyboard, then using the Emotiv EPOC headset. Participant must move robot alpha forward over the A1 yellow line until the robot alpha crosses the A2 yellow line. The participant must move robot alpha backwards over yellow line A3 until robot alpha crosses over yellow line A4. When the robot alpha has completely passed over the A4 yellow line the test case is complete for robot alpha.

[Course A] The user first moves the robots using the keyboard, then using the Emotiv EPOC headset. Participant must move robot beta forward over the B1 yellow line until the robot beta crosses the B2 yellow line. The participant must move robot beta backwards over yellow line B3 until robot beta crosses over yellow line B4. When the robot beta has completely passed over the B4 yellow line the test case is complete for robot beta. The user has a maximum of 15 minutes to complete this test case.

Test Case Completion Code:

1. Mark session sheet A1 when participant crosses robot alpha over A1 yellow line
2. Mark session sheet A2 when participant crosses robot alpha over A2 yellow line
3. Mark session sheet A3 when participant crosses robot alpha over A3 yellow line
4. Mark session sheet A4 when participant crosses robot alpha over A4 yellow line
5. Mark session sheet B1 when participant crosses robot beta over B1 yellow line
6. Mark session sheet B2 when participant crosses robot beta over B2 yellow line
7. Mark session sheet B3 when participant crosses robot beta over B3 yellow line
8. Mark session sheet B4 when participant crosses robot beta over B4 yellow line



Level 7 :

No Training

Requirements :

- Participant must perform three test cases.
- Participant has a maximum time to complete a action, if time passes move robot for participant and move onto next action.

Action Task Timing :

- Participant has a maximum total of 20 minutes to complete the task.
- If the participant is struggling and is making no progress the researcher may end the session after 15 minutes has passed.

Test Case Description:

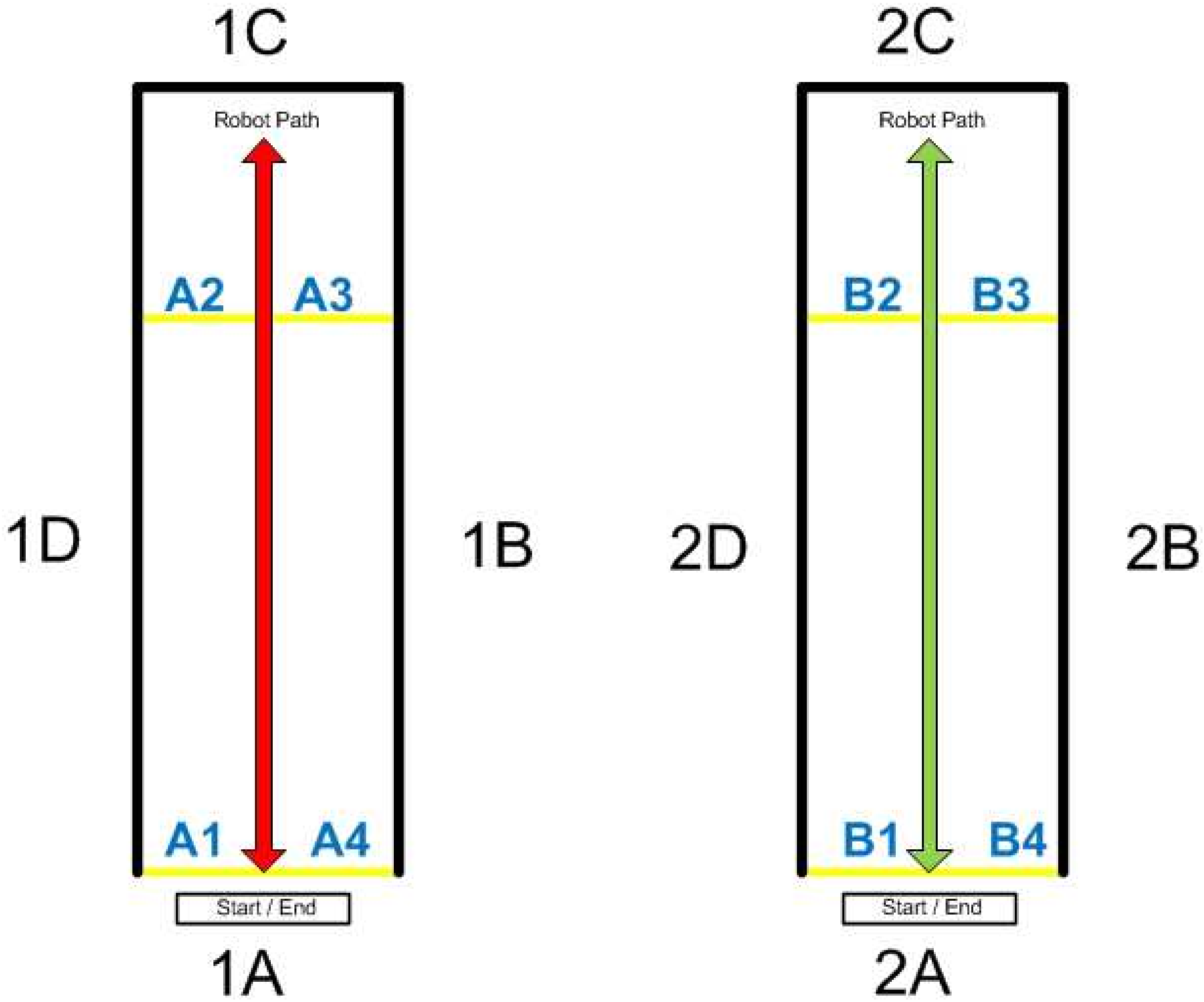
[Course B] The user first moves the robot alpha using the keyboard, then using the Emotiv EPOC headset. Participant must move robot alpha forward over the A1 yellow line until the robot alpha crosses the A2 yellow line. The participant must rotate the robot alpha right and then move the robot alpha across the A3 yellow line. The participant moves the robot alpha forward until it crosses the A4 yellow line, then the participant must turn the robot alpha right. The participant moves the robot alpha forward until it crosses both the A5 yellow line and the A6 yellow line. When the robot alpha has completely passed over the A6 yellow line the test case is complete.

[Course B] The user first moves the robot beta using the keyboard, then using the Emotiv EPOC headset. Participant must move robot beta forward over the B1 yellow line until the robot beta crosses the B2 yellow line. The participant must rotate the robot beta right and then move the robot beta across the B3 yellow line. The participant moves the robot beta forward until it crosses the B4 yellow line, then the participant must turn the robot beta right. The participant moves the robot beta forward until it crosses both the B5 yellow line and the B6 yellow line. When the robot beta has completely passed over the B6 yellow line the test case is complete. The user has a maximum of 20 minutes to complete this test case.

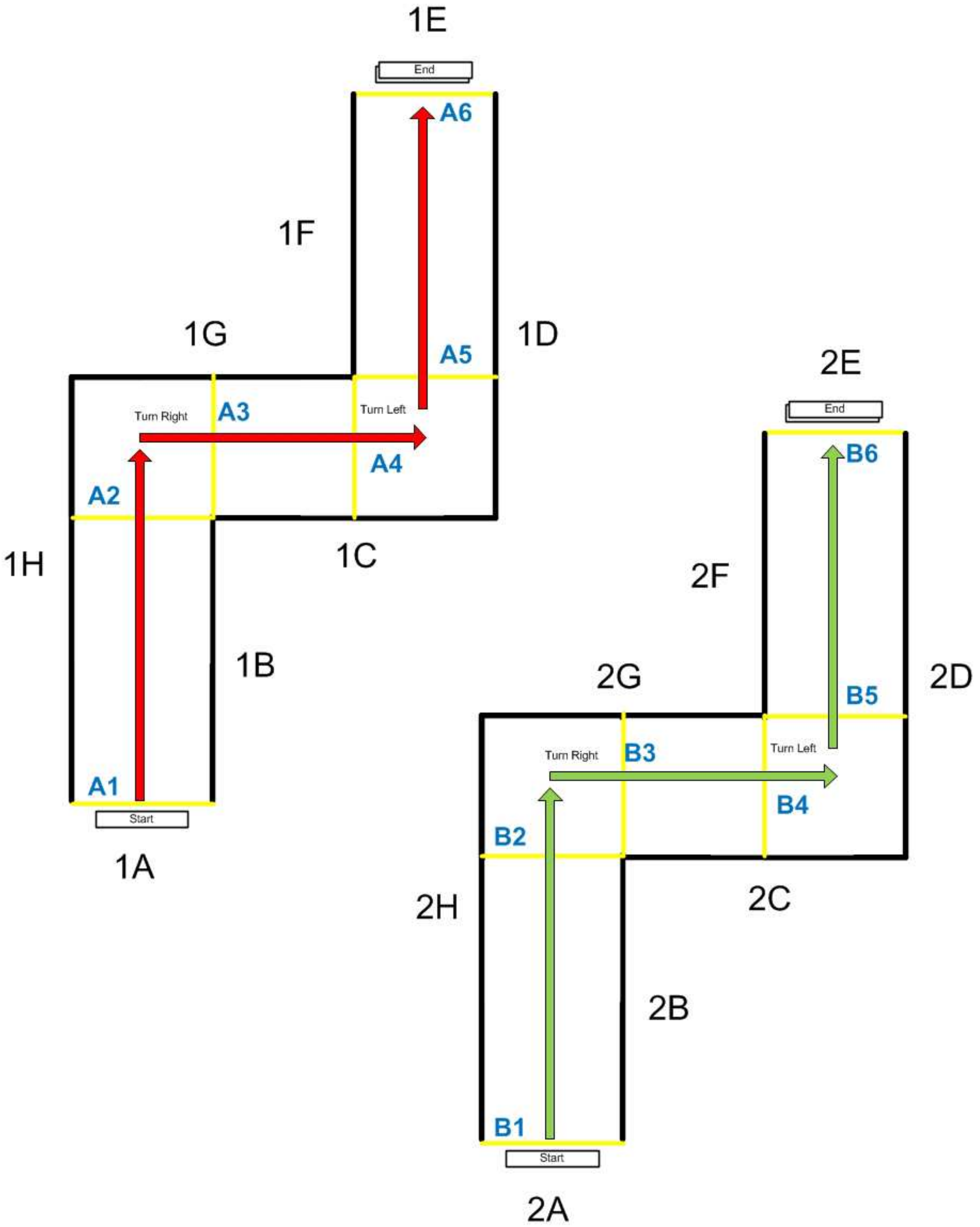
Test Case Completion Code:

1. Mark session sheet A1 when participant crosses robot alpha over A1 yellow line
2. Mark session sheet A2 when participant crosses robot alpha over A2 yellow line
3. Mark session sheet A3 when participant crosses robot alpha over A3 yellow line
4. Mark session sheet A4 when participant crosses robot alpha over A4 yellow line
5. Mark session sheet A5 when participant crosses robot alpha over A5 yellow line
6. Mark session sheet A6 when participant crosses robot alpha over A6 yellow line
7. Mark session sheet B1 when participant crosses robot beta over B1 yellow line
8. Mark session sheet B2 when participant crosses robot beta over B2 yellow line
9. Mark session sheet B3 when participant crosses robot beta over B3 yellow line
10. Mark session sheet B4 when participant crosses robot beta over B4 yellow line
11. Mark session sheet B5 when participant crosses robot beta over B5 yellow line
12. Mark session sheet B6 when participant crosses robot beta over B6 yellow line

COURSE A


1C
Robot Path
A2
A3
1D
1B
A1
A4
Start / End
1A
2C
Robot Path
B2
B3
2D
2B
B1
B4
Start / End
2A

COURSE B



1E
End
A6
1F
1G
1D
A5
Turn Right
A3
Turn Left
A4
A2
1H
1C
1B
A1
Start
1A
2E
End
B6
2F
2G
2D
B5
Turn Right
B3
Turn Left
B4
B2
2H
2C
2B
B1
Start
2A

Appendix F

Usability of BCI and the effects of differing access to technology

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ABSTRACT

Brain-Computer Interfaces (BCIs) technologies have been used to enable disabled persons to interact with a computer in order to communicate or to control a prosthesis. BCI research that uses electroencephalography (EEG) has proven that the technology can be used successfully for severely disabled patients using a number of techniques such as a P-300 speller. However research of this kind has consisted mainly of demonstrations using a few users on specialised hardware and software. These users often have been intimately involved in the project and are friends, family or the researchers themselves. This has resulted in very little information on how this technology applies to the general population. This study proposes to determine whether the level of access a person has to technology will affect a participant's performance using BCIs. The study will use participants from a rural area and participants from a city area for comparison. A second research goal is to determine if there is a performance difference between the genders when using a BCI device. Finally the study will try to ascertain if an affective aspect of a participant will affect their performance using a BCI device.

This study is centered on the Emotiv EPOC headset. The Emotiv is a non-invasive BCI device which includes a full set of supporting software tools. The study aims to find out how the device performs with two distinct test groups based on their differing access to technology. The affective state of the participants will be monitored and recorded throughout the sessions to see if there is a correlation between a participant's affective state and their performance.

Participants will be required to use the Emotiv headset to control a Mindstorm NXT robot through a series of actions. These actions are forwards, backwards, turn right, turn left and activate robot. A participant will learn an action and then run through three trials using the action. After the participant has learned all the actions needed they will attempt to complete two obstacle courses. The first course requires the participant to move a robot forwards and then backwards within boundaries. The second course is significantly more difficult, incorporating two turns, a right and a left turn. These courses will require the participant to navigate two robots to the end of their prospective courses. During these sessions the affective measurements from the headset and the participant's performance during the trials will be closely monitored and recorded.

A pilot study was conducted with two participants and has shown some interesting initial results. It does appear that frustration affects participant's performance negatively. Despite not understanding how the technology functions, all participants so far have been able to use the headset with little coaching. The imagery used by participants is very interesting, for example to turn right a participant imagined rotating a chess piece in their hand.

Following the success of the pilot study, the main study will be conducted with a larger group of participants and a complete statistical analysis done to draw conclusions from the data.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human Factors and Features *Human information processing.*

General Terms

Performance, Experimentation, Human Factors

Keywords

BCI, Emotiv, Usability

Effectiveness with EEG BCIs: Exposure to traditional input methods as a factor of performance

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ABSTRACT
Brain computer interfaces (BCIs) are traditionally used to assist disabled persons to communicate. These specialised systems are often designed to function for specific individuals with little regard for the use of a BCI with able bodied individuals. To help address the issue this study compared two groups of participants who were classified based on their varying exposure to traditional input methods. The usability metric effectiveness, in terms of error rate, was compared while using the Emotiv or a keyboard to move a robot. The results indicated that exposure to traditional input methods is not a factor in the effectiveness of the BCI. Thus a person can effectively use the BCI without prior knowledge of computers which broadens the acceptability of the interface. Therefore a BCI, like the Emotiv, could serve as an alternative communication channel for able bodied individuals.

Categories and Subject Descriptors
H.1.2 [**User/Machine Systems**]: Human Factors and Features *Human information processing.*

General Terms
Performance, Experimentation, Human Factors

Keywords
Brain-Computer Interface, Emotiv, Usability

INTRODUCTION

Natural User Interfaces (NUIs) are proposed as a replacement or supplement for traditional input methods with alternative methods of interaction [25]. There are a number of alternative input interfaces to the traditional input method of the mouse and keyboard. These include eye tracking [21], voice recognition [30] and an EEG-based Brain Computer Interface (BCI) [5]. BCIs in particular offer an innovative alternative to a traditional input method such as the keyboard and could form a valuable addition to NUIs.

BCIs are generally designed to assist a few individuals with disabilities with little consideration for the usability of the system with able bodied persons. Although there has been a recent trend in BCI research [17] to investigate how a BCIs performs for able users, these studies are still too few [7]. BCIs are a natural fit for NUIs as the research field came into play to investigate the replacing or supplementing of traditional input methods with alternative methods of interaction [25].

The development of commercially available BCIs [6] enabled this study to contribute to the available data by comparing the performance of two groups of able-bodied participants using two control methods, namely an EEG BCI and a keyboard. The two groups were classified based on their varying exposure to traditional input methods as measured by a questionnaire. The study's results in terms of effectiveness, defined as the task error rate, indicated whether exposure to a traditional input method was a significant factor in performance and gave insight on the usability of an EEG BCI for both groups.

The following section will give brief background information on the Emotiv (the EEG BCI used) motivating its use for this study. The study methodology will be covered followed by a discussion of the effectiveness results. The final section will draw conclusions from the results and the future work that can be based on this study will briefly be mentioned.

BACKGROUND

The origins of BCIs date back to the original work by Berger [2] who was among the first scientists to discover that the human brain can create a signal that is readable by a machine. This signal became known as EEG and since the signal reflects brain activity, a person's intent can be extracted from these signals. Wolpaw [29] categorised EEG BCIs into two broad categories, namely invasive and non-invasive BCIs. Both BCI categories receive neurophysiological rhythms from electrode sites and translate these signals into commands a machine can understand. The difference is that invasive BCIs have the electrodes surgically implanted into the scalp, while non-invasive BCIs have the electrodes rest on top of the scalp. An example of an invasive BCI is the study by Hochberg et al [9] who implanted an array of electrodes into two quadriplegic patients' brains at their hand representation areas to allow them to move a cursor on a computer screen in several directions. Invasive BCIs have a superior spatial resolution when compared to non-invasive BCIs but the inherent dangers of neural surgery require that invasive techniques should only be used as a last resort [27]. As such a non-invasive EEG BCI was utilised for this study.

EEG signals are usually measured by affixing 10-20 electrodes to a scalp using a head band or cap. This arrangement is known as the 10-20 standard setup [11]. EEG BCIs are known to have

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an estimated transfer rate of around 5-25 bits of information per minute [29]. This information rate is too slow to control complex machinery, such as a prosthetic arm, but is fast enough for complex tasks that are not time sensitive such as asynchronous control of a robotic arm. A number of EEG BCI types exist, of which the most prominent are slow cortical potentials (SCPs), P300 evoked potentials, Steady-State Visual Evoked Potentials (SSVEP) and sensorimotor rhythms (mu, alpha and beta rhythms).

SCPs are slow potential variations consciously generated in the cortex of a human [1]. Humans can learn to voluntarily regulate SCPs after in depth operant training that uses immediate feedback and positive reinforcement [3]. A P300 evoked potential is a positive peak signal generated in the brain approximately 300 milliseconds after a response to target stimuli that has occurred unexpectedly. This stimulus can be visual or auditory, as long as it is unexpected to the participant and is the basis for a P300 BCI [1, 22]. A SSVEP is the natural brain response elicited when the retina is excited by visual stimuli, typically flickering LED lights. When a SSVEP is detected by the SSVEP BCI the signal can be detected and used to call a command [15]. Sensorimotor rhythms are rhythms detectable by an EEG BCI and are referred to as alpha, beta and mu rhythms. Alpha rhythms are measured from between 8 Hz to 13 Hz, beta rhythms are observable from 12 Hz to 30 Hz and mu rhythms are measured from 8 Hz to 12 Hz [1, 10].

Of particular interest to this study are the rhythms produced by the brain when imagining movement. When a person physically moves, or imagines the same movement, a similar rhythm is produced [13]. The rhythm produced ranges in the upper alpha and lower beta rhythm bands [20]. As the participant's used for this study were all novices (never having used a BCI before), the most natural approach available was required and thus imagined movement was used.

An EEG BCI was needed that could detect sensorimotor rhythms and was usable outside of a clinical setting. The Emotiv EPOC headset was well suited for this purpose. The Emotiv has a disadvantage compared to custom built dedicated research BCIs, namely that the headset has less than a quarter of the channels used in most studies. The headset uses only 14 sensors which is in the region of one tenth of the data sample rate available to larger setups [16]. However Lotte et al. [14] indicated that an EEG BCI can be used with as little as three sensors, which mitigated this disadvantage.

Furthermore, the Emotiv has been used in a number of studies that indicated that the headset was acceptable for research. The Emotiv was tested for its viability to detect P300 events by Rosas-Cholula et al. [23] and was found to be valid. Petersen et al. [19] successfully tested the viability of the Emotiv paired with a smart phone as a mobile EEG. In a study directly related to the current one, Vourvopoulos and Liarokapis [26] used imagined movement and the Emotiv with 54 participants to measure the responsiveness of the Emotiv to navigate a robot. Although their study was qualitative in nature, the response was positive. Consequently these studies validate the use of the Emotiv for the study discussed in this paper.

METHODOLOGY

Participants

This study compared two groups of participants that moved a robot using two different control methods, namely the Emotiv and the keyboard. Participants were sampled from two different areas, namely a rural and an urban area. These groups were identified based on their varying exposure to traditional input methods, which was verified based on their expertise which was a measure of frequency and length of use [24]. Two questions were used on the recruitment questionnaire, one to measure frequency (scale 1-6) and the other to measure duration (scale 1-7), the answers of which were multiplied to get an expertise rating. The rural group was found to have a low expertise (SD=16.45) while the urban group had a high expertise (SD=41.25). The rural group was recruited from a university campus which services a rural community and was identified as Group A. The urban group was recruited from the main campus of the same university and was identified as Group B. For both groups a convenience sample was used via a self-selection method [28]. Each sample set was made up of an equal number of males and females to make up a total group of twenty participants per group. The low retention rate of the study meant Group A was reduced to ten participants and Group B was reduced to eight participants. However, according to Nielsen [18], for a HCI study the minimum recommended participants is five thus the participant count for this study was adequate.

Experimental Methodology

The test instrument used for this study was a custom written program that consisted of three major components: a control panel used to train the movements with the Emotiv, an interface to manage the sessions and a database which logged the session data for later offline analysis. The Emotiv was configured to detect motor imagery as this was believed to be the most natural approach for the participants. The hardware used was a Microsoft based personal computer with a standard keyboard and mouse setup. The robots used were a pair of programmable Mindstorm NXT's (Figure 1).

Figure 1: The pair of Mindstorm NXT robots used in this study.

This study consisted of four usability test sessions. Each session tested a single movement (move the robot forward (level 1), move the robot backward (level 2), rotate right (level 3) and rotate left (level 4)). Each session was designed to take no longer than forty-five minutes. Of the forty-five minutes, thirty minutes was used for training the action and the other fifteen minutes used for the user tests. The user tests were all performed in sets of three with each lasting no longer than five minutes. Each session trained and tested a single movement, with increased difficulty in later sessions as a result of more movement choices being available to the participant resulting in a higher cognitive load on the participant. The first four contact sessions were in preparation for a final course that would test all four actions, the results of which are beyond the scope of this paper. The levels were analysed using repeated measures ANOVAs.

RESULTS

In order to measure effectiveness the sample data was analysed using repeated measures ANOVA. The sample data was tested for normality using the Shapiro Wilk test and sphericity using Mauchly's test. All four levels of the data were tested and found to be not normal. A nonparametric alternative exists called the Friedman test but was not used as it lacks statistical power with small samples [8]. However, repeated measures ANOVA are robust to violations of normality [12] and thus the test was used regardless of the data's underlying distribution. In terms of the sphericity of the data the degrees of freedom were adjusted using the Huynh-Feldt factor (Table 1) if the data was not spherical [12].

Table 1: Mauchly's test

Level Tested	Result
Level 1	$\chi^2 = 0.941$, $p > 0.05$
Level 2	$\chi^2 = 0.739$, $p > 0.05$
Level 3	$\chi^2 = 16.240$, $p < 0.01$*
Level 4	$\chi^2 = 0.000$, $p < 0.01$*

**Significant Result*

Table 2: Repeated measures ANOVAs usability test results for the four levels.

Factor	Level Tested	Result
Error rate	Level 1	$F_{(2, 62)} = 0.383$, $p > 0.05$
	Level 2	$F_{(2, 56)} = 2.520$, $p > 0.05$
	Level 3	$F_{(1.594, 47.824)} = 5.528$, $p < 0.05$*
	Level 4	$F_{(1.130, 26)} = 1.371$, $p > 0.05$
Group	Level 1	$F_{(1, 31)} = 0.008$, $p > 0.05$
	Level 2	$F_{(1, 28)} = 1.956$, $p > 0.05$
	Level 3	$F_{(1, 30)} = 0.099$, $p > 0.05$
	Level 4	$F_{(1, 24)} = 3.429$, $p > 0.05$
Control Method	Level 1	$F_{(1, 31)} = 10.462$; $p < 0.01$*
	Level 2	$F_{(1, 28)} = 1.878$; $p < 0.01$*
	Level 3	$F_{(1, 30)} = 6.363$; $p < 0.05$*
	Level 4	$F_{(1, 24)} = 3.429$; $p > 0.05$

**Significant Result*

Table 2 reports the results for the effectiveness evaluated using a repeated measures ANOVA. For the user tests variance was detected between the sequential tests for level 3, an indicator that there may be a learning effect or improvement in performance.

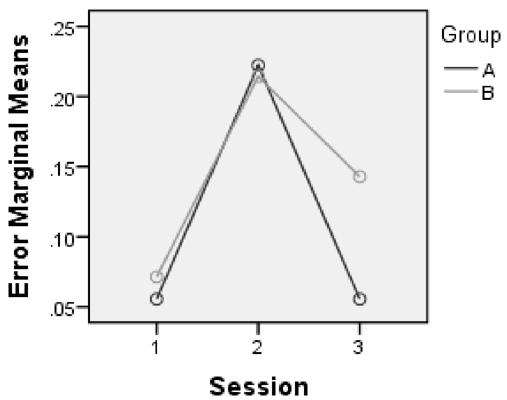

Figure 2: Mean error rate for Group A and Group B for level 3 using the Emotiv.

A closer analysis of level 3 (Figure 2) indicated that the variance detected was from the higher error rate during test 2 compared to the other usability tests for both groups. Since an improvement in performance would appear as a negative trend there was no evidence of improvement of performance for level 3. Thus there was no significant improvement for any of the actions over the three usability tests for all four levels.

The factor group (Table 2) reported no significant results for all four levels. Therefore whether a participant has low or high exposure to a traditional interface had no significant influence on their effectiveness using the Emotiv. This could indicate that exposure to traditional input methods was not a factor when using the Emotiv to move a robot.

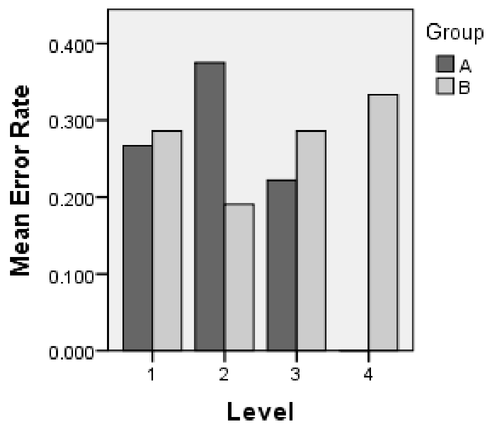

Figure 3: Error rate mean per level using the Emotiv.

The final factor analysed was the control method (keyboard or Emotiv) used, that is whether there was a significant difference between controlling a robot with a keyboard or the Emotiv. The results indicated that aside from level 4, the difference in the error rate between both control methods for the four levels was significant. Considering Figure 3 it was clear that the keyboard outperforms the Emotiv by a wide margin.

It was interesting to note that level 2 (move backwards) was Group A's worst performance and Group B's best. From this point onwards Group A improved while Group B got steadily worse. It is possible that as Group B had a relatively high exposure to traditional input methods that their best practices schema was violated. In cognitive theory it is theorised that a person creates a best practices schema on how to work an interface. If a new interface is not congruent to the pre-existing schema it can cause disorientation for the participant, resulting in reduced performance [4]. Therefore Group B might have struggled to develop a working schema which affected their performance.

CONCLUSION

There are relatively few studies on the usability of EEG BCIs for able bodied individuals. To help address this shortfall, this paper compared the effectiveness of two groups of participants classified on their exposure to traditional input methods while using two control methods. The keyboard was found to outperform the Emotiv and there was no evidence of improved short term performance across user tests with either group using the Emotiv. These results indicate exposure to traditional input methods does not influence a participant's effectiveness when maneuvering a robot using an EEG BCI. This was an encouraging result as knowledge of computers was thus not a requirement for the interface. This in turn broadens the applicability of the EEG BCI as an alternative to traditional input methods.Future work for this study includes analysing efficiency using time, subjective measurements and the analysis of a course that uses all four movements available to the groups. Suggested work related to this study also includes a longitudinal study to measure learnability and studies done outside of a South African context to confirm results. As the availability of EEG BCI technology to the public becomes more prevalent, so does the need to understand how this technology will impact how the public utilises the BCI as an interface.

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Summary

A brain-computer interface (BCI) is a device that uses neurophysiological signals measured from the brain to activate external machinery. BCIs have traditionally been used to enhance the standard of living for severely disabled patients. This has resulted in a shortage of data on how BCIs perform with able-bodied individuals. There has recently (2012) been a trend towards BCI research involving able users but these studies are still too few to make a substantial impact. Additionally, traditional input methods are being replaced or supplemented by alternative natural modes of interaction and these natural interactions have become known as NUIs. To investigate the suitability of a BCI as a NUI, this study used the Emotiv headset to provide direct measurement of a participant's performance while performing tasks similar to wheelchair manipulation in order to determine whether a participant's access to traditional input methods influences their performance.

Thus, the main aim of this study was to investigate the usability of an Emotiv for robot navigation. Additionally, the study aimed to discover whether a user's performance differed when using a keyboard compared to the Emotiv as well as investigating whether there was improvement of performance in the short term for a user through repetitive use of the Emotiv.

In order to compare the usability of the Emotiv to a keyboard the participants were placed into groups based on their exposure to traditional input methods. This was verified based on their individual expertise rating, which was a measure of frequency and length of use. The test instrument used consisted of a written program that navigated a pair of Mindstorm NXT robots across a custom designed test course. Data was collected via usability testing which measured learnability, efficiency and effectiveness. Efficiency was measured as the time taken to complete a task while effectiveness was a measure of the errors made by a participant when completing a task.

Results indicated that there was no significant difference between the groups' efficiency and effectiveness when using the Emotiv to complete a task. Thus, a user's previous experience with a traditional input method does not influence a user's performance with an Emotiv when navigating a robot. This result indicates that the interface is intuitive to use and, therefore the Emotiv could be suitable as a NUI. The results for the usability metrics

efficiency and effectiveness indicated that there was a significant difference between the performances with the Emotiv and a keyboard. The results show that, with the Emotiv, participants took more time to complete a task and made more errors when compared to a keyboard. This discrepancy was attributed to cognitive theory as it is believed that the participants violated their preformed schema which affected their performance. However, the participants quickly became comfortable with the Emotiv which supports the evidence that the interface is intuitive to use. For neither the usability metrics efficiency nor effectiveness was a significant improvement detected with repetitive use of the Emotiv. Thus, repetitive use of the Emotiv to navigate a robot does not improve a user's performance over a short period of time.

These results indicate that in terms of efficiency and effectiveness the keyboard is the superior interface. The results also revealed that a participant's performance is not affected by their exposure to traditional input methods when utilising a BCI. Thus, the Emotiv is intuitive to use and appears suitable for use as a NUI. This study proved that the Emotiv is an intuitive interface and can be used with little to no previous experience.

Opsomming

'n Brein-rekenaar-koppelvlak (BCI) is 'n toestel wat gebruik maak van neurofisiologiese seine gemeet van die brein om eksterne masjinerie te aktiveer. BCIs is tradisioneel gebruik om die lewenskwaliteit van erg gestremde pasiënte te verbeter. Dit het tot 'n tekort aan data gelei oor hoe BCIs met nie-gestremde individue vaar. Daar is onlangs (2012) 'n tendens, in die BCI navorsingsrigting, met die gebruik van nie-gestremde gebruikers maar hierdie studies is nie genoeg om 'n beduidende impak te hê nie. Daarbenewens is die tradisionele invoer metodes vervang of aangevul deur alternatiewe, natuurlike maniere van interaksie . Die natuurlike interaksies staan bekend as NUIs.

So, die belangrikste doel van hierdie studie was om die bruikbaarheid van 'n Emotiv vir robot navigasie te ondersoek. Verder het die studie gepoog om vas te stel of 'n gebruiker se prestasie verskil wanneer die gebruik van 'n sleutelbord in vergelyking met die Emotiv sowel as die ondersoek of daar ' n verbetering van die prestasie in die kort termyn vir 'n gebruiker deur middel van herhaalde gebruik van die Emotiv.

Ten einde die bruikbaarheid van die Emotiv na 'n sleutelbord te vergelyk die deelnemers in groepe op grond van hul blootstelling aan tradisionele insette metodes geplaas . Dit is bevestig op grond van hul individuele kundigheid gradering , wat 'n mate van frekwensie en lengte van gebruik. Die toets instrument gebruik het bestaan uit 'n skriftelike program wat navigator 'n paar van Mindstorm NXT robots in 'n persoonlike ontwerp toets kursus. Data is ingesamel deur middel van gebruikers toets wat gemeet leerbaarheid , doeltreffendheid en effektiwiteit. Doeltreffendheid is gemeet as die tyd wat dit neem om 'n taak te voltooi , terwyl doeltreffendheid was 'n mate van die foute wat gemaak word deur 'n deelnemer tydens die voltooiing van 'n taak.

Resultate het aangedui dat daar geen beduidende verskil tussen die groepe se effektiwiteit en doeltreffendheid by die gebruik van die Emotiv 'n taak te voltooi. Dus, 'n gebruiker se vorige ondervinding met 'n tradisionele invoer metode nie 'n gebruiker se prestasie beïnvloed met 'n Emotiv toe opgevolg 'n robot. Hierdie resultaat dui daarop dat die koppelvlak is intuïtief te gebruik en dus die Emotiv geskik as 'n NUI kan wees . Die resultate vir die bruikbaarheid statistieke doeltreffendheid en het aangedui dat daar 'n beduidende verskil tussen die optredes saam met die Emotiv en 'n klawerbord . Die resultate dui daarop dat , met die Emotiv , deelnemers het meer tyd om 'n taak te voltooi en het meer foute in vergelyking met 'n klavier. Dit verskil is toegeskryf aan kognitiewe teorie as dit word geglo dat die deelnemers geskend hul gevormde skema wat hul prestasie beïnvloed . Die deelnemers het egter vinnig gemaklik met die Emotiv wat ondersteun die bewyse dat die koppelvlak is intuïtief te gebruik geword het. Want ook die bruikbaarheid statistieke doeltreffendheid of effektiwiteit was 'n aansienlike verbetering bespeur met herhalende gebruik van die Emotiv . So , herhalende gebruik van die Emotiv 'n robot om te navigeer nie 'n gebruiker se prestasie oor 'n kort tydperk van die tyd te verbeter.

Hierdie resultate dui daarop dat in terme van doeltreffendheid en effektiwiteit van die sleutelbord is die beter koppelvlak. Die resultate het ook getoon dat 'n deelnemer se prestasie is nie geraak deur hul blootstelling aan tradisionele insette metodes toe behulp van 'n indeks . Dus, die Emotiv is intuïtief te gebruik en geskik vir gebruik as 'n NUI verskyn. Hierdie studie bewys dat die Emotiv is 'n intuïtiewe koppelvlak en kan gebruik word met min of geen vorige ondervinding.