An Offline Multi-Class Auditory P300 Brain-Computer Interface Using Principal and Independent Component Analysis

by

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Declaration

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Abstract

A Brain-Computer Interface (BCI) provides technology that allows communication and control for people who are unable to interact with their environment. Functional electrical stimulation (FES) devices are developed to improve or restore functionality to an impaired nervous system. For patients suffering from serious neural degenerative disorders, a BCI provides a hands-free means of controlling FES devices. A P300 BCI exploits the fact that external or internal stimuli provide a robust recognition response in the brain's electrical activity which may be recorded by an electroencephalogram (EEG) to act as a control signal. The increased amplitude of a target P300 determines the extent to which it may be separately distinguished and thus its efficiency as a signal controller in a P300 BCI. An auditory P300 benefits those patients whose visual systems have been compromised. Traditional P300 paradigm approaches do not effectively lend themselves to FES integration.

This thesis investigated a multi-class auditory P300 BCI as a step towards FES applicability. A multi-class P300 paradigm approach provides degrees-of-freedom in operating an FES device over the traditional P300 paradigm. Accuracy in classification of target P300s contributes to the paradigm's applicability in a 'real' environment. The computational effectiveness of the paradigm can be enhanced through signal processing prior to classification. A combination of principal component analysis (PCA) and independent component analysis (ICA), together with a method of enhancing the P300 properties through temporal and spatial manipulation are investigated as a means of improving classification accuracy. The combination of these techniques and the use of a multi-class P300 paradigm presents a different approach as a step towards FES applicability in an auditory BCI.

Auditory multi-class and binary equal-probability (based on the traditional) P300 paradigms are proposed for 'real' environment application. An offline

synchronous study was conducted on 15 subjects. By using a combination of PCA and ICA signal processing techniques, together with temporally and spatially manipulated data, single-trial classification accuracies of up to 68% and 77% were produced for the multi-class and binary equal-probability auditory P300 paradigms respectively (however, by counterbalancing the subject task order, the marginal difference between the two results could have changed). Alternatively, signal processing reliant on only PCA, produced single-trial average results of over 95%.

In conclusion, the proposed multi-class auditory P300 paradigm using a combination of PCA and ICA with temporal and spatial P300 enhancement does not provide results which are conducive to FES application. However, comparative research using PCA provides accuracies for scope of further work into online asynchronous systems.

Publications and Presentations Associated with the Research

Bentley, A.S.J., Andrew, C.M. & John, L.R. 2009, "Increasing User Functionality of an Auditory P3 Brain-Computer Interface for Functional Electrical Stimulation Application", IFMBE Proceedings, Singapore, pp. 687-690.

Bentley, A.S.J., Andrew, C.M. & John, L.R. 2008, "An Offline Auditory P300 Brain-Computer Interface Using Principal and Independent Component Analysis Techniques for Functional Electrical Stimulation Application", EMBS 2008, Vancouver, pp. 4660-4663.

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Terminology

Abstractions (in order of appearance)

Medical

EEG	-	electroencephalogram
ADL	-	activity of daily living
SCI	-	spinal cord injury
EMG	-	electromyogram
SCP	-	slow cortical potential
MSSVER	-	multiple SSVER
USSVER	-	unitary SSVER
ALS	-	amyotrophic lateral sclerosis
CLIS	-	complete locked-in state
ERP	-	event-related potential
SSVER	-	steady-state visual-evoked response
SMR	-	sensorimotor rhythm
VEP	-	visual-evoked potential
EOG	-	electrooculogram
ERS	-	event-related synchronisation
ERD	-	event-related desynchronisation

Systems

BCI	-	Brain-Computer Interface
FES	-	Functional Electrical Stimulation
PC	-	personal computer
GSN	-	Geodesic Sensor Net
A/D	-	analog-to-digital

Mathematical

ICA	-	independent component analysis
PCA	-	principal component analysis
S/N	-	signal-to-noise (ratio)
BSS	-	blind-source separation
SVM	-	support vector machine
FA	-	factor analysis
IC	-	independent component
GSI	-	Thornton's (Geometric) Separability Index

PPV	-	positive predictive value
NPV	-	negative predictive value
NN	-	neural network
LDA	-	linear discriminant analysis
LSVM	-	linear SVM
LOOCV	-	leave-one-out cross-validation
DC	-	direct current
ANN	-	artificial NN
ELM	-	extreme learning machine
ANOVA	-	analysis of variance

Miscellaneous

ACT	-	Alternative Control Technology
OP	-	oddball paradigm
SCCN	-	Swartz Center for Computational Neuroscience
IFCN	-	International Federation of Clinical Neurophysiology

Scalp Regions

Fz	-	Frontal ('z' refers to the midline)
Cz	-	Central ('z' refers to the midline)
Pz	-	Parietal ('z' refers to the midline)

Glossary

(terms are described in footnotes and appendices, however the more commonly used terms are explained below)

accuracy	-	a measure of the degree of closeness to the actual (or true) value for all conditions i.e. the ratio between correctly identified conditions and all identified conditions expressed as a percentage
degrees-of-freedom	-	the number of independent movements that constitute a proposed functional movement
paradigm	-	a concept use to describe and interpret a proposed (or heuristic) experimental setup
'real' environment	-	a scenario that is equivalent to real-life

1 Introduction

1.1 Background

Many of us take activities of daily living (ADLs) for granted. Simple functional movements such as grasping or standing do not require any conscious form of control. All these processes are managed by an intricate network of neurons and their associated cognitive procedures. From conception, neuronal activity governs the functional movement required to perform essential tasks inherent to the systems of our body. However, for many people suffering from neurological disorders, these 'simple' activities form the basis upon which the quality of daily life is determined.

Functional movement forms the end product of a complex interconnected array of neuronal activity affecting muscles. The required movement is achieved via feedback control between sensors throughout the body and the related centres of the brain. Neurological disorders disrupt these communicative pathways hindering the control and performance of tasks.

Neuroprostheses are developed to restore or improve functionality of an impaired nervous system. These are artificial devices that act as sensory (such as the cochlear implant) or motor prostheses. One such method is that of functional electrical stimulation (FES). This method uses electrical current to activate nerves innervating muscles associated with functional motor movement of extremities that have been affected by paralysis. This may be due to a spinal cord injury (SCI), head injury, stroke, or neurological disorder. Paralysis is a result of interference between the brain and the muscles associated with the movement (Crago et al. 1996). "FES is a rapidly developing technology having the potential to overcome some of these problems" (Boord et al. 2004) without the need for:

1. replacement prosthetics; and,

2. orthotics with externally powered motors.

It attempts to aid the somatic nervous system in restoring motor functionality. Today FES “is available as a clinical tool in muscle activation used for picking up objects, for standing and walking, for controlling bladder emptying, and for breathing” (Boord et al. 2004). For example, FES has thus far been used as an aid in stepping and standing in people with paraplegia and to restore hand grasp in people with tetraplegia. Patients suffering from the above mentioned disorders face significant lifestyle challenges and “the technology has the potential to reduce the lifetime cost” of the problem (Boord et al. 2004).

FES is a means of restoring lifestyle challenges in people with SCIs. Many people are not able to perform basic ADLs and thus a means of restoring this loss of functionality equates to restoring lifestyle independence (Grill 2000). By stimulating the neuromuscular system using electric current, functional movements may be enhanced or produced. Restoring this motor function using FES requires methods of how these FES systems are controlled.

1.2 The Problem

In general neuroprostheses (including FES) are controlled by a command interface that measures a modality so as to maintain voluntary control. FES control signals can be extracted from muscles (Electromyogram, EMG) and the brain (Electroencephalogram, EEG), however FES devices employing EMG are specific to individuals who have conscious control over muscular function or to individuals not requiring the use of the muscles that are activating the EMG in performing the FES movement. Often the task of the user is to select a pre-programmed sequence to achieve an automatic procedural response *without* the need for conscious intervention. A problem arises in that many FES responses require control systems which are practical and beneficial or complementary to people suffering from serious neural degenerative diseases and disorders. A means of bypassing these damaged neural pathways with cognitive control (i.e. EEG) presents itself as an attractive means of restoring functional movement.

The control systems need to include:

1. a hands-free approach (which may allow for provision of functional support if required e.g. postural);
2. a robust and reliable means of obtaining and issuing commands; and,
3. a 'real' environment applicability.

In recent years, attempts have been made at utilising the electrical signals generated by the brain as a means of initiating communication. The intention was to help people with severe motor disabilities to communicate by providing them with a new supporting tool for communication and control (Curran, Stokes 2003). Advances in machine learning, signal processing, and hardware equipment have made possible the development of brain computer communication systems, or Brain-Computer Interfaces (Wolpaw et al. 2002). Brain-Computer Interfaces (BCIs) provide a hands-free means of controlling electrical devices by using signals derived directly from brain activity. Thus they provide a significant potential for the operation of FES devices (Pfurtscheller et al. 2003).

A BCI is a direct communication pathway between a brain and an external device. Its aim is to provide an additional voluntary channel of output for the brain. One of the major aims and motivations of BCIs has been to help patients suffering from conditions such as Lou Gehrig's disease, brain and spinal injuries, cerebral palsy, and other neurodegenerative diseases, which inhibit physical control, but which leave intellectual capabilities unhindered.

The aim of a BCI is three-fold:

- to create an assistive device for communication and control for disabled people or people suffering from neurodegenerative diseases;

- to diagnose and monitor neurological disorders; and,
- to improve the man-machine interface.

The main elements that constitute (and ultimately determine the performance) of a BCI include:

- the stimulus type;
- the control signal; and,
- the signal processing technique.

Factors such as concentration, fatigue, emotion, relaxation, frustration, distraction, motivation, intention and other thoughts may affect BCI control (Curran, Stokes 2003). Other elements to consider may include ergonomic and, to a lesser extent, aesthetic design.

Changes in neuronal activity are affected by internal and external stimuli. Internal stimuli are governed by 'invisible' thoughts and processes, while external stimuli moderate these changes by movement, vision, or hearing. Most BCIs are operated via motor imagery or a visual stimulus (Table 1.1).

Table 1.1 BCI types and their relative input modalities.

BCI type	Bandwidth (Hz)	Input type	Reference
Graz	> 8	Mental imagery	(Pfurtscheller et al. 2000)
Albany	> 8	Visual	(Wolpaw, McFarland & Vaughan 2000)
Slow cortical potential	< 8	Mental imagery	(Birbaumer et al. 2000)
Frontal Beta	25 – 28	Mental imagery	(Lauer, Peckham & Kilgore 1999)
Hill	0.1 – 40	Auditory	(Hill et al. 2005)
Multiple steady-state visual-evoked response (MSSVER)	> 6	Visual	(Middendorf et al. 2000)
Unitary steady-state visual-evoked response (USSVER)	> 6	Visual	(Middendorf et al. 2000)
Mind Switch	8 – 13	Eye-closure	(Craig et al. 1999)
Pfurtscheller	15 – 19	Mental imagery	(Pfurtscheller et al. 2003)
Spatial auditory multi-class P300	0.1 – 250	Auditory	(Schreuder, Blankertz & Tangermann 2010)
Nine-class P300	*unspecified*	Auditory	(Hőhne et al. 2010)

Utilising imagery (or internal stimuli) as the operating modality (or stimulus type) requires training on the part of the user i.e. it is user specific (Boord et al. 2004). The resultant waveforms may carry unwanted signal echo distortion and artefact production due to the stimulus being associated with an action in the motor area of the cortex and the actual produced motor movement being different to the imagined movement. For example, a patient required to imagine foot movement in order to operate a FES device which stimulates a hand grasp as the end product, may find it difficult to continue imagining the foot movement whilst visual feedback is that of a hand grasp movement. Additionally, with long periods of immobility, the degeneration of pyramidal cells in the motor cortex can make it difficult to 'imagine movement'. Other waveforms, such as the self-regulation of slow cortical potentials (SCPs) utilised by Birbaumer et al. (2000), provide multi-class outputs, but require extensive training on the part of the subject and the accuracy of classification is greatly diminished.

Problem 1	Many FES-BCI systems require extensive training.

BCIs need to operate according to an inherent cognition pattern. Neural activity is composed of various frequency dependent bands. An extremely robust brain waveform is that of the P300, which is elicited in specific paradigms and can be modulated according to experimental variations. The P300 is regulated via a subject's recognition of useful target information. Vision and hearing provide the basis for (external) stimuli in P300 BCIs.

The practicality of using an auditory stimulus over a visual stimulus in a 'real' environment is unmatched. To give an example: it is much easier to perform a functional movement (e.g. performing a hand grasp using FES) listening to earphones than it is to perform the same functional movement while watching a screen in front of you. For subjects with intact vision, a functional movement that requires some form of additional BCI visual control would distract the user's attention away from the task at hand (in the case of a visual stimulus). Many neurological disorders may lead to loss of vision or gaze control (e.g. amyotrophic lateral sclerosis, ALS), especially in the case of patients that suffer from a complete locked-in state (CLIS) – all voluntary muscular control is lost. Complete immobility of the eye (e.g. due to CLIS) can mean that steady visual signals fade i.e. the input to a visual system (Hill et al. 2005). More often than not the auditory system is uncompromised.

Problem 2	Visual stimuli are not complementary to application in a 'real' environment.

The P300 appears as an increase in EEG amplitude at a series of electrode locations (frontal midline - Fz, central midline - Cz, and parietal midline - Pz) post stimulus and provides BCIs with a binary classification output of either being present or not. Sellers and Donchin (2006) utilised the P300 in a spelling paradigm BCI and it has since proven an extremely efficient decision medium in BCIs. That system was, however, limited by only providing a binary output, but this hindrance may be overcome by adaptation of the device being manipulated. By altering the traditional single-stimulus or oddball P300 paradigms (which ultimately can only provide two possible outcomes – target or non-target) the user selectivity may be increased to incorporate more than two options (e.g. enabling the user to select one of three possible outcomes from the paradigm), thus increasing the number of independent degrees-of-freedom. Traditional P300 multi-class (or three-stimulus) paradigms favour the decreased probability of the target stimulus against non-target (or standard) stimuli which isn't complementary to 'real' environment applicability due to the target being pre-chosen. Therefore, ideally the user should be able to choose the target (from equal probability stimuli) in order to perform the appropriate response associated with that target.

Problem 3	FES systems ideally require multiple degrees-of-freedom (the traditional P300 paradigms provide only two possible outcomes) with paradigms that are applicable in a 'real' environment i.e. where the target is initially chosen from the available stimuli without manipulating the paradigm to favour the target of choice.

Visual stimulus BCIs have thus far proven to have superior processing capabilities over auditory BCIs (Nijboer et al. 2007). However, a study conducted by Bennington and Polich (1999) comparing the P300 ERP from auditory and visual stimuli concluded that auditory stimuli produce more robust P300 components than visual stimuli in *passive* task situations (little difference was noted in the *active* tasks); however strong P300 components can be produced via visually compelling items (such as a subject's name). The effects of habituation on the P300 amplitude are also less pronounced for auditory stimuli in passive task scenarios (Bennington & Polich, 1999). Treder & Blankertz (2010) investigated overt and covert attention in a visual ERP speller paradigm. Overt (e.g. eye movement) resulted in better performance than covert (e.g. visual periphery) attention (Treder, Blankertz 2010). A similar test was conducted by Schreuder et al. (2010) using an auditory spatial paradigm whereby spatial recognition of auditory cues through different speakers in varying locations resulted in increased performance over a single speaker. The results proved the possibility of effectively utilising auditory stimuli in BCIs in instances where visual efficacy is compromised (Schreuder, Blankertz & Tangermann 2010). Auditory generated P300s experience a relatively low signal-to-noise (S/N) ratio. Therefore more efficient, robust and reliable processing techniques need to be envisaged for auditory systems (Katayama, Polich 1999).

Problem 4	Auditory P300s have a lower S/N ratio and hence aren't comparable in performance to visual P300s.

Signal processing procedures have been investigated to improve the accuracy of classification in BCIs. Recently a technique known as independent component analysis (ICA), which is able to separate independent signal sources through matrix manipulation, has been tested in BCIs with promising results (Bugli, Lambert 2007). It uses a method of blind-source separation (BSS) to extract independent signals from linearly mixed data. Another processing technique known as principal component analysis (PCA) theoretically rotates matrices orthogonally so as to highlight the maximum variance associated with data. PCA also presents an attractive method of data reduction. Variables presenting minimal variance may be eliminated (with some loss of information). Thus PCA may be used as a data reduction technique prior to ICA to simplify processing (Bugli, Lambert 2007). These two methods of signal processing (and a combination thereof) have been extensively explored by Bugli and Lambert (2007) and Dien et al. (2007). Temporal and spatial manipulation of data based on *a priori* knowledge of a waveform proves to be an effective means of improving the accuracy of classification (Xu et al. 2004).

1.3 Proposed Solution

The main elements of a FES-BCI system are dependent on the output requirements of the FES system being controlled. Hence for a BCI-controlled FES device, the factors that need to be taken into account for each BCI element include:

1. a control signal that is robust and requires as little training as possible (identified through **Problem 1**);
2. a stimulus type that is applicable in a 'real' environment and that can be utilised in as many neurological disorder instances as possible (identified through **Problem 2**);
3. a means of providing degrees-of-freedom for performing functional movements (identified through **Problem 3**); and,

4. a signal processing technique that allows for accurate classification of the control signal (identified through **Problem 4**).

By taking into account the associated factors required for FES-BCI systems and the identified problems above, the proposed solutions (introduced in section 1.2) include:

1. a robust P300 waveform as a control signal;
2. utilisation of an auditory stimulus for P300 generation;
3. a multi-class paradigm providing degrees-of-freedom and 'real' environment applicability; and,
4. investigating the use of PCA and ICA techniques with temporal and spatial manipulation to improve the signal processing of the P300 paradigms.

1.4 Statement

This thesis focuses on an auditory P300 BCI with a multi-class paradigm as a step towards potential FES application using a combination of PCA and ICA techniques[1]. Comparisons are made between visual and auditory classifications of the P300 and a proposed 'real' environment experimental paradigm is explored in an attempt to increase output selectivity (and hence degrees-of-freedom) for FES systems. Additionally, the classification accuracies of utilising no signal processing, PCA alone, and a combination of PCA and ICA with and without temporal and spatial manipulation are to be compared.

[1] Additionally employing the technique of temporally and spatially manipulating the EEG data.

1.5 Objectives

As indicated in 1.4, this thesis investigates an auditory P300 BCI. More specifically, the research aims are:

1. to test a proposed multi-class P300 paradigm as an alternative to a binary equal-probability (based on the traditional) P300 paradigm (using the proposed S/N enhancing signal processing techniques) as a step towards FES applicability;

2. to determine whether an auditory stimulus for the P300 generation could be used as an alternative to a visual stimulus; and,

3. to determine the single-trial classification accuracy using the signal processing steps of a combination of PCA and ICA with temporal and spatial manipulation compared with no signal processing, PCA alone, and a combination of PCA and ICA without spatio-temporal manipulation.

1.6 Scope and Limitations

The purpose of this research was to establish the classification accuracy of the auditory P300 BCI paradigms in an offline single-trial state – a key step to building a FES applicable direct BCI system with multiple degrees-of-freedom. An offline BCI provides the basis upon which real-time asynchronous analysis can be developed. By testing the P300 BCI algorithm synchronously offline, large datasets could be utilised to improve accuracy and this allows the channels providing the best discernible information to be identified for further research into online systems. Offline analysis not only allows for 'cleaner' data via manual rejection of artefact contamination, but also helps in determining parameters for the algorithm. This additionally allows for improved signal processing as a step towards an online asynchronous approach. A synchronous system accommodates the knowledge of mental activity detection in advance. Hence the scope has been limited to an offline synchronous BCI.

Auditory and visual P300 experimental paradigms are compared to assess the algorithm's applicability and functionality in a 'real' environment. A binary equal-probability P300 paradigm along with a proposed multi-class P300 paradigm is explored to support this investigation. For this study, speed is not measured because the focus is primarily on accuracy of classification by using a high resolution system to capture EEG and the signal processing identified through the literature.

This thesis is further limited to the use of non-invasive scalp EEG for the detection of mental activity. Additionally no actual FES testing was conducted using the proposed algorithm as the investigation focused on the potential or feasibility as a step towards application. The algorithm was also only tested on able-bodied subjects. A comparison of the different EEG devices for BCI implementation was not done in this study. Also only a linear support vector machine (SVM) was used to classify the P300 waveforms.

Please note the Harvard method of referencing was used in writing up the research.

1.7 Plan of Development

Chapter 2 delves into the literature and research behind BCI systems for FES control and continues by exploring the elements of the P300, auditory stimuli, multi-class paradigms and the signal processing techniques. The experimental paradigm, the materials used and the proposed method are discussed in Chapter 3. Chapter 4 present the results which are discussed in Chapter 5. Conclusions and recommendations for future work appear in the final chapters.

2 Literature Review

There are major benefits of utilising a hands-free control method for FES systems. Performing functional movements often require the cooperative coordination of extremities. Many patients require the use of their hands or other extremities in movement or applications and thus it isn't possible to use these in operating a command system where their coordination with other functional movements is required[2]. The control of FES systems are predominantly not based on feed-forward systems (Sinkjaer et al. 2003). Thus 'thought' or rather measured electrical activity in higher cortical structures presents an attractive control system for neuroprostheses (or FES). "Neuroprostheses operate through a command interface that measures some modality over which voluntary control is maintained, and translates this to a specific operation of the prosthesis" (Boord et al. 2004).

A BCI is a means of communicating via voluntary neural activity generated by the brain and recorded using invasive (implanted electrodes) and non-invasive (EEG) techniques (refer to Appendix A for an explanation of BCIs). Output pathways are independent of nerves and muscles (Vallabhaneni, He 2004). BCIs have the potential of providing incomparable aid to people suffering various neurological and communicative problems. With increased processing capabilities, simple practicalities of life may be restored for these people. Unfortunately current designs lack the efficacy required to be utilised in a 'real' environment. BCIs are able to control computers or external devices by only requiring the regulation of brain activity (Birbaumer et al. 2006). An additional benefit of BCIs is that they provide a

[2] For example, the arms and hands may be required to provide postural support when FES is applied to leg muscles for ambulation.

platform from which prosthetic, orthotic, and FES systems or devices may be controlled.

Sinkjaer et al. (2002) stated that "despite substantial progress in development and new knowledge, many challenges remain to be resolved to provide a more efficient functionality of FES systems. The most important task of these challenges is to improve control of the activated muscles through open loop or feedback systems… BCI systems hold great prospects, but require further development of … clinically more acceptable technologies" (Sinkjaer et al. 2003). This challenge still faces BCI systems today.

2.1 BCI systems for FES control

Two distinct methods of BCI control have been established. The first involves endogenous variance over the EEG spectrum, which is adjusted and determined by the user through extensive training. The second involves the variance of exogenous components of event-related potentials[3] (ERPs) in neural activity, within which the P300 falls (Donchin, Spencer & Wijesinghe 2000). These two techniques have been employed in BCIs for control of FES devices. See Appendix B for a full explanation of EEG including ERP.

In today's technological era, people suffering from neurological disorders affecting functional movement still face significant lifestyle challenges. Developing an EEG-based FES device for use by people with *severe* motor disabilities and neurological disorders still remains a hindrance. Measured biopotentials of the brain using EEG contain the feed-forward control required for FES devices.

[3] A brain's electrical activity response to thought, memory, expectation, attention, perception or changes in the mental state, is known as an ERP. These potentials are caused by "higher" processes as opposed to evoked potentials which relate to physical stimulus.

"However, development of faster and clinically more acceptable technologies for interfacing the brain is needed" (Sinkjaer et al. 2003), therefore requiring systems that are robust, accurate and applicable in a 'real' environment.

BCIs have thus far proven effective as a control structure for FES, but they are limited to a certain extent (or degree) by the error rates common to many paradigms. Implantable electrodes (such as BrainGate (Cyberkinetics)) have a higher S/N ratio and present a better topographical representation of the brain's biopotentials, but have adverse affects on subjects if long-term use is required. The recorded signals are transmitted to external units and processed to extract relevant control signals. The recording of biopotentials from the brain and the relevant hardware are discussed in Appendix C.

In 2003 Cyberkinetics Inc. developed BrainGate – a microchip implanted in the brain used to monitor brain activity. FES systems can utilise BrainGate as a command controller. Thus far it has been used to move a robotic arm and a computer cursor, but there is an expectation that it will be employed to control the user's environment through a personal computer (PC) (Cyberkinetics). Although BrainGate provides many of the factors required for effective FES control (refer to section 1.3) it unfortunately presents an invasive technique of monitoring brain activity and its long-term effects are yet to be determined. Wolpaw et al. (2002) were of the opinion that because implanted techniques are highly invasive, "the threshold for clinical use will initially be higher than in surface BCI systems".

Pfurtscheller et al. (2003 and 2005) proposed a method using an EEG-based asynchronous[4] BCI for control. A tetraplegic patient could "induce bursts of beta

[4] An asynchronous BCI operates on an uncued or user-driven command system. This offers more natural human-machine interaction, but is difficult to implement due to the user's control intention and timing usually being unknown. Hence a vast amount of training and adaptation is required to achieve a certain amount of accuracy (Tsui, Gan 2007).

oscillations by imagination of foot movement" to restore a hand grasp function. The "oscillations were recorded in a one EEG-channel configuration, band-pass filtered and squared" and if detected would allow the user to switch through phases to perform the functional movement. A breakdown of the system is shown in Figure 2.1.

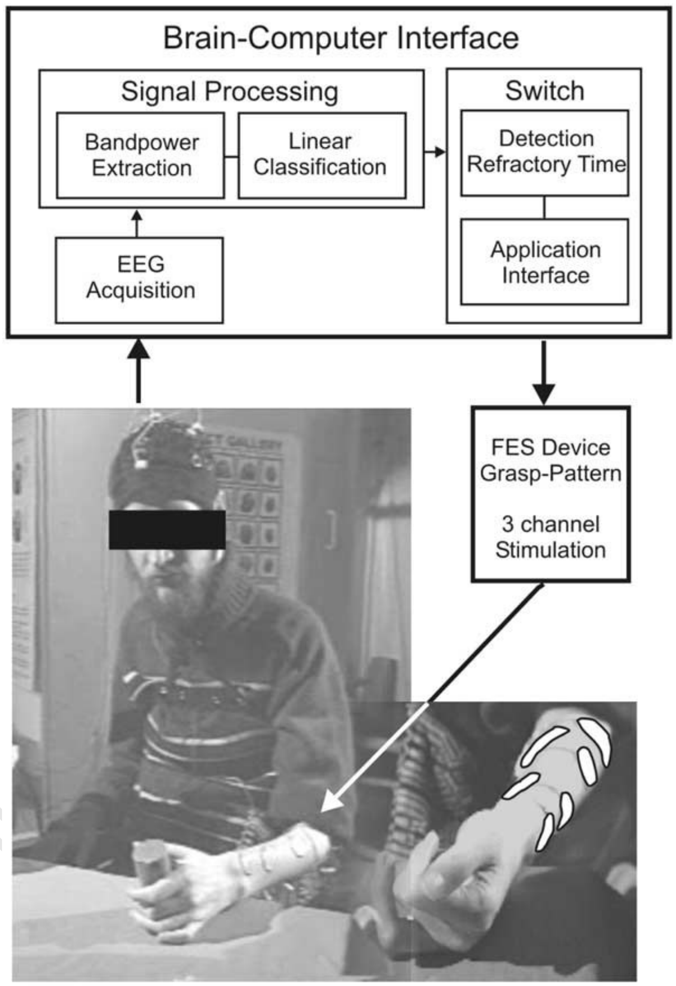

Figure 2.1 Example of a bipolar EEG-based BCI recording from a tetraplegic patient. The system operates a FES device with three pairs of surface electrodes. The six positions of the electrodes are indicated. The patient is able to grasp a cylinder with the paralysed hand when the FES is switched-on by beta burst in the EEG induced by foot movement imagination (Pfurtscheller et al. 2003).

A non-invasive technique was used to record the EEG and the output of the BCI would determine the switching between the different sequences to perform the hand grasp. A threshold comparator would detect the bursts of beta oscillations. By using only two electrodes and recording one bipolar EEG channel, muscle activity artefact production was reduced. Thus EMG activity can somewhat be eliminated from the BCI output signal (Pfurtscheller et al. 2003). Different imagery motor tasks produce varying levels of beta oscillations and this combined with maximising the performance of the BCI by utilising as few electrodes as possible will determine the viability of the system in real-life situations (Pfurtscheller, Neuper & Birbaumer 2005).

The system employed by Pfurtscheller et al. (2003 and 2005) has the advantage of not requiring an external stimulus. However, considerable training time[5] was required in customising the setup to the user's specifications. Due to this training requirement, the apparatus was also therefore subject-specific. It should also be noted that FES currents may affect EEG signals. Many of the electrical signals in the brain used by BCIs are affected by extremity (and therefore muscular) movement (creating artefacts in the EEG) and thus being able to limit this degradation in signal quality is of importance. In a lot of cases an echo effect in the midcentral cortex is created due to the resultant movement of the hand (Pfurtscheller et al. 2003). This signal contamination (although somewhat reduced through the use of the electrode and channel configuration) produces a problem in motor areas of the cortex and thus active and passive movements reduce the integrity of the signal where biofeedback isn't utilised.

The Alternative Control Technology (ACT) program of the Air Force Research laboratory tested a steady-state visual-evoked response (SSVER) system as an effective communication medium for BCIs. Users "are trained to exert voluntary control over the strength of their SSVER" (Middendorf et al. 2000) to operate a FES

[5] To be specific, 55 training sessions were required (Pfurtscheller et al. 2005).

system. Middendorf et al. (2000) adopted a discrete binary control system so that changes in the SSVER resulted in control actions occurring at fixed intervals. The response was elicited using a visual stimulus modulated at a fixed frequency. Visual biofeedback enabled users to learn to control their SSVER amplitude. The logic techniques enabled smooth and stable control to be formed from the noisy SSVER. Two thresholds were used for binary control (i.e. raising the SSVER above or below the two thresholds resulted in different actions). The stimulus was generated by modulating the luminance of a visual input at a certain frequency (13.25 Hz). An accuracy of 95.8% was acquired by three able-bodied participants.

The advantage of the system used by Middendorf et al. (2000) was that it proved accurate by providing visual biofeedback and wasn't affected by extremity movement. However, the system used visual stimuli and also required training for the users to learn to control their SSVER (Boord et al. 2004).

An important characteristic that may be included in a FES-BCI operating system is that the FES should ideally incorporate a control method that can issue commands asynchronously (i.e. whenever the user wishes). The BCI must therefore be able to distinguish between the intended command and other brain activity at any time. Presently the Mind Switch[6] is the only BCI that has been demonstrated to operate in an asynchronous environment (Boord et al. 2004) while not requiring extensive training, as is the case with asynchronous motor imagery control systems developed by Pfurtscheller et al. (2003 and 2005) or the MSSVER BCI developed by Middendorf et al. (2000). Continuous[7] and synchronous[8] control environments have the limitation of requiring the person to constantly attend to the control task. The

[6] The Mind Switch monitors alpha-band (8 – 13 Hz) signals from the part of the cortex most sensitive to eye-closure (Boord et al. 2004).
[7] The BCI generates commands continuously to update the state of the device.
[8] Stimuli are presented at a fixed time interval to indicate time windows when the user's response is measured.

accuracies of the various asynchronous, synchronous and continuous BCIs can be seen in Table 2.1.

Table 2.1 BCI Characteristics and Accuracy Measures of some FES-BCI systems (modified from Boord et al. (2004)). Note: accuracy is calculated as in section 3.2.3.3 i.e. the average of sensitivity and specificity.

BCI type	Control type	Input type	Accuracy	Reference
Graz	Synchronous	Mental imagery	98	(Pfurtscheller et al. 2000)
Albany	Continuous	Visual	86	(Wolpaw, McFarland & Vaughan 2000)
SCP	Synchronous	Mental imagery	75	(Birbaumer et al. 2000)
Frontal Beta	Continuous	Mental imagery	94	(Lauer, Peckham & Kilgore 1999)
MSSVER	Asynchronous	Visual	92	(Middendorf et al. 2000)
USSVER	Continuous	Visual	96	(Middendorf et al. 2000)
Mind Switch	Asynchronous	Eye-closure	86	(Craig et al. 1999)

Ideally FES techniques need to operate with command interfaces that can receive graded and state-switching responses, which are determined asynchronously and additionally do not interfere with the user's ability to operate the system.

Boord et al. (2004) stated that "many signals used by BCIs are affected by extremity movement, and are unlikely to be suitable for neuroprostheses". Additionally the corollary indicates that "using signals outside of motor areas make them less susceptible to disturbance from active or passive movement of limbs" (Boord et al. 2004).

Control accuracy in general-purpose BCIs has always come under scrutiny. Recent signal classification advances have improved the accuracies but ultimately the end-product is far from perfect. Bayliss et al. (2004) proposed a method of improving control accuracy. The presence of a P300-like signal in response to target objects provides a means of automatic error correction (Bayliss 2003). Piccione et al. (2006) established the P300 as a control signal in both healthy and paralysed patients as well as its efficacy in not requiring time-consuming training. The theory of the P300 is explored in Appendix D.

2.2 P300-based BCIs

P300 BCIs provide a relatively robust means of obtaining cognitive information and communication without relying on peripheral nerves and muscles. For this reason it has widespread use in people with disabilities. However, the P300 paradigm has thus far not been used for FES control. The fact that the P300 is a robust waveform and provides very high classification accuracies, equates to an attractive FES controlling paradigm. A phase controlled FES system, similar to the paradigm employed by Pfurtscheller et al. (2003 and 2005), but utilising a P300 approach, presents a scenario for research.

Many P300 speller paradigms adopt the layout shown in Figure 2.2.

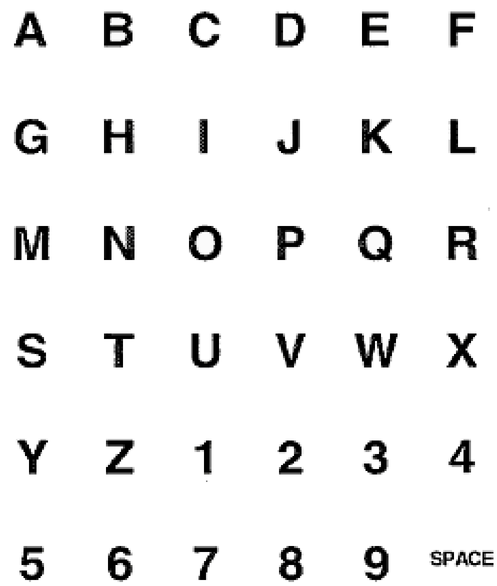

Figure 2.2 A popular interface for P300 spellers (colours have been inverted from Donchin, Spencer & Wijesinghe (2000)).

Farwell and Donchin (1988) were the first to propose communication with a computer through the P300 ERP by adapting an oddball paradigm[9] (OP) as the 'operating principle' behind the first ever P300-BCI. The paradigm allowed users to select one of 36 symbols in a 6 by 6 matrix. By repeatedly flashing (or intensifying) rows and columns in the matrix, subjects were able to select the target character when it was highlighted (see Figure 2.3). A rate of 2.3 characters per minute was achieved.

[9] "In an OP, the participant is presented with a Bernoulli sequence of events, each belonging to one of two categories. The participant is assigned a task that cannot be performed without a correct classification of the events. If the participant indeed attends to the sequence, and one of the categories occurs less frequently than the other, events from the rare category elicit the P300 component of the event-related potential (ERP)" (Sellers, Kubler & Donchin 2006).

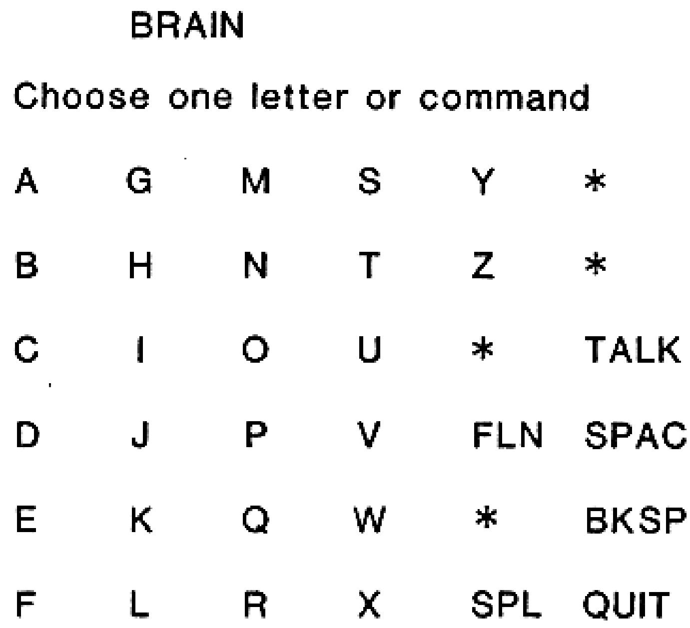

Figure 2.3 The display used by Farwell and Donchin (1988). The rows and columns of the matrix were flashed alternately. The subject was able to spell the word 'BRAIN' (modified from Allison (2003)).

The University of South Florida Cognitive Psychophysiology Laboratory devised a P300-BCI speller as a communication tool. Sellers et al. (2006) developed a four-choice system: Yes, No, Pass, and End, and incorporated these with three presentation techniques: visual, auditory, and a combination of the two. The four-choice paradigm revealed that ALS patients classified an auditory stimulus more accurately than a visual stimulus. The tests indicated that both the visual and auditory P300-based BCIs can serve as non-muscular communication devices in both ALS and non-ALS users (Sellers, Kubler & Donchin 2006).

Since its initial conception, devices such as remote control aids, enhanced word spellers (Wang, Guan & Zhang 2005), and cursor control applications (Piccione et al. 2006) have been tested on healthy subjects and used to assist people with 'locked-in' syndrome[10]. The performance of the systems can reliably control, in real-time, the devices with relatively high accuracy (Wolpaw et al. 2002).

The study conducted by Polikoff et al. (1995) laid the groundwork for cursor control applications using the OP of P300 elicitation. The user was required to fixate on a central point. By counting the number of times a chosen compass direction was briefly replaced by an asterisk, the direction of cursor movement could be determined. A null stimulus was included in which no asterisk appeared. EEG data was recorded from the Fz, Cz, and Pz electrodes (or electrode locations). See Appendix E for electrode nomenclature and the 10-20 locations.

The first P300 Speller adopted by Farwell and Donchin (1988) produced feasible but not conclusively accurate results for use with an FES system (Sellers, Kubler & Donchin 2006). The four-choice method used by Sellers et al. (2006) produced the question of whether it could serve as a FES communication tool – indicating the importance of accuracy when considering viable 'real' environment systems.

Recently a lot of research has gone into developing tools for patients suffering from CLIS (where all volitional control over muscles is lost). BCI presents one of the few technologies that provide a communication pathway for these patients. The visual modality relies on subjects being able to use their eyes. Eye movements, blinks and adjustment of focus require volitional muscles and hence a visual stimulus BCI does not present a viable solution for CLIS patients or those suffering from the neural degenerative disease ALS[11] (Hőhne et al. 2010).

[10] These people have cognitive functionality but have lost the ability to speak and move their extremities.
[11] ALS causes a decrease in sight, but the ability to hear is usually unaffected.

The choices, employed by Sellers et al. (2006) that made up these degrees-of-freedom are limited by the disadvantages of visual stimuli for FES systems (apart from the auditory components investigated). Most P300-based BCI approaches use the visual modality for stimulation. For patients suffering from ALS this might not be the preferred choice because of sight deterioration. Moreover using a modality different from the visual one minimises interference with possible visual feedback (Schreuder, Blankertz & Tangermann 2010).

Additionally the degeneration of pyramidal cells in the motor cortex (due to long periods of immobility) may make it difficult to 'imagine movement' in mental imagery BCIs. Also the fact that in severe cases the entire visual modality becomes unreliable as a control mechanism: "the eyes cannot adjust focus; the fovea cannot be moved to inspect different locations in the visual scene, meaning that most of a given image will stimulate peripheral regions of retina which have low spatial resolution" (Hill et al. 2005). The responses of retinal ganglion cells are temporally band-pass, therefore eye immobility resulting in fading of steady visual signals. Additionally, a study conducted by Brunner et al. (2010) casts doubt on visual P300 BCIs due to the fact that they are eye-gaze dependent. Hence their application for patients suffering from a lack of control over eye-gaze (e.g. CLIS) is limited (Brunner et al. 2010). Thus this represents considerable motivation to explore the P300 response to auditory stimuli. This method of signal control also does not require the extensive training that mental imagery techniques require and the resultant device is not as user specific. However, habituation effects result in P300 reduction which can be a major disadvantage of P300 BCIs (Romero, Polich 1996).

2.3 Auditory BCIs

Researchers have delved into the idea of providing auditory feedback BCIs. Nijboer et al. (2007) explored the feasibility of a sensorimotor rhythm (SMR) BCI with auditory feedback. Volunteers trained to increase or decrease their SMRs. These are mu rhythms (see Appendix A) in the alpha band (8 – 12 Hz) that change amplitude with motor movement or with motor imagery. A comparison between visual and auditory feedback was investigated. It was discovered that although initially visual feedback was superior in performance, there was a decrease in performance difference with increased training sessions (i.e. there was notably no difference after the third session). They concluded "that with sufficient training time an auditory BCI may be as efficient as a visual BCI" and that "mood and motivation play a major role in learning to use a BCI" (Nijboer et al. 2007). Advantages of auditory stimuli over visual and imagery stimuli are discussed in Hill et al. (2005).

Similar results (with respect to a decrease in visual feedback) were obtained by Pham et al. (2005) using self-regulation of SCPs to operate a BCI. A performance comparison was carried out between visual, auditory or cross-modal visual-auditory feedback systems as a means of enhancing the SCPs. Visual stimuli produced the best performance results, followed by the auditory stimuli. The difference was partly due to self-produced positivity and a larger SCP response variability in the auditory condition. Pham et al. (2005) suggested that increased selective attention to simultaneously produced auditory stimuli resulted in smaller cortical positivity. SCPs are prone to be affected by artefact distortion and contact impedance is critical for low frequency to DC measurements (Tallgren 2006).

Hill et al. (2005) introduced "An Auditory Paradigm for Brain-Computer Interfaces" indicating that users could modulate EEG signals in a single trial by the conscious direction of attention. They implemented a paradigm allowing users to make a binary decision according to auditory stimuli (see Figure 2.4). The auditory (or acoustic) stimulus consisted of two periodic sequences of 50 ms square-wave beeps presented from two separate speakers placed on the left and right. These beeps varied in frequency. By producing deviant tones of left and right sound signals of different periods, subjects could elicit BCI control. It was suggested that auditory ERPs could be used as part of a single-trial BCI.

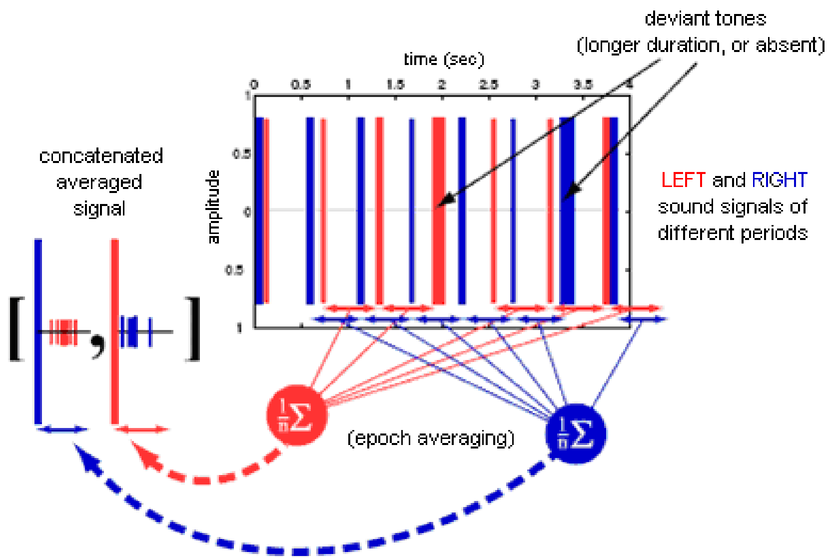

Figure 2.4 Schematic illustration of the acoustic stimuli used in the experiment conducted by Hill et al. (2005).

2.4 Multi-Class Auditory P300 BCIs

FES compensates for degrees-of-freedom in performing functional movements. For example, hybrid orthoses combine FES and mechanical braces. The braces reduce the number of degrees-of-freedom and provide support for weaker muscles; while the FES is applied to the muscles to act on these remaining degrees-of-freedom (Thrasher, Popovic 2008). Complex motions that require precise and fine control are yet to be perfected. FES systems ideally require multi-class selectivity (for multiple degrees-of-freedom) which the traditional P300 paradigm doesn't provide (it only provides a binary output). Variations to the traditional paradigm might provide a control mechanism that enhances the accuracy of existing FES-BCI systems.

Schreuder et al. (2010) developed an auditory P300 BCI paradigm using spatially distributed auditory cues in a field. Accuracies of over 90% were obtained for most conditions with averaging over 15 sub trials per location. However when the stimuli were presented through a speaker (effectively cancelling the spatial properties), the selection scores dropped below 70%. This presents a disadvantage for FES utilisation.

A 9-class two-dimensional P300 BCI decision medium was proposed by Hőhne et al. (2010). Healthy subjects were required to spell a sentence when presented with auditory stimuli of three different pitches and three different locations (left earphone, right earphone, and both), thus presenting a two-dimensional 3 by 3 decision medium. Accuracies of up to 92% were obtained for most subjects. Two subjects' accuracies dropped to zero when they reported that they couldn't concentrate anymore (Hőhne et al. 2010). However, the advantages include more degrees-of-freedom, little or no training, and a realistic approach to 'real' environment application.

2.5 Signal Processing for BCIs

Efficient BCIs based on P300 evoked potential have been implemented on disabled and able-bodied subjects. Processing methods such as factor analysis (FA), PCA, and ICA have been used to extract the P300 component of the ERP from noise. Signal processing of P300 can therefore increase classification efficiency.

Due to the low S/N ratio for raw EEG, averaging of trials is used in many ERP (and P300) processing techniques. To achieve a sufficiently high S/N ratio, at least 20 P300 trials are needed (Cohen, Polich 1997). Averaged event-related potentials (ERPs) provide a simplified means of analysing and filtering EEG data to reveal disclosed information in the recordings. Ideally, however, the goal[12] is to develop a system whereby a single trial may be accurately classified using a BCI. Pattern

[12] The goal, in general, for FES applicable BCIs, is to create real-time responses.

recognition approaches using classifiers to detect error potentials (Blankertz et al. 2002) and amplitude threshold criterion methods, aim to create robust single-trial detection procedures in multi-channel EEG systems. This requires very efficient computational and detection methods, which eliminates the efficacy of ERP averaging techniques. PCA and ICA have proven to be the methods of choice when analysing EEG data because of their ability to extract information from signal mixtures. These modalities may be incorporated into a P300 BCI as a means of creating a single-trial communication medium.

2.5.1 PCA and ICA in BCIs

Kennedy et al. (2000) describe an invasive alternative to surface EEG recorded BCI devices (Kennedy et al. 2000). Surface electrode recordings are subject to many more artefact distortion properties. Thus advanced processing techniques, or enhanced signal recording capabilities, are required to attempt to overcome these limitations. P300 waveforms are extracted from EEG signals more often than not by PCA or ICA. The two processing techniques also present an attractive means of separating artefact from EEG. Visual P300 waveforms have a greater S/N ratio than auditory P300 waveforms. Thus PCA and ICA present a useful means of extracting an auditory P300 from noise. Vallabhaneni et al. (2004) utilised PCA for feature extraction in raw EEG data which produced good classification results but further work needed to be done on improving the accuracy for application to online BCIs. PCA was applied on spatial as well as temporal dimensions in two steps.

Using PCA for auditory ERP analysis in schizophrenic patients was explored by Vinther (2002). PCA was used to reduce the number of channels from 7 to 2. Over 90% of the variance was maintained by using only 2 channels and hence the amount of data required for classification was vastly improved.

In the research conducted by Hill et al (2004), variation of the experimental paradigm improved the accuracy but was still relatively insufficient to be used in a practical environment. In 2005 the accuracy of their results was improved by implementing ICA and normalisation techniques to process the EEG data. The dimensionality of the classification was reduced using recursive feature elimination techniques (averaging followed by ICA and normalisation) and a SVM was then used to classify the data. There was a marked improvement in the performance of the BCI with decreased classification error rates. Although this system lacked multi-class outputs, it proved that a synchronous auditory BCI based on ERP (such as the P300) could possibly be used on a single-trial basis. The ICA processing of the data improved classification accuracy. Experiments were performed using different techniques in which no ICA was used in the processing and then ICA was included. There was a marked increase in accuracy (of between 3% and 37%) with the inclusion of ICA (Hill et al. 2005).

Erfanian et al. (2004) used ICA for feature extraction of a single-channel EEG. The results proved that the method improved the classification accuracy of EEG patterns.

ICA in combination with matched filters, averaging and threshold techniques, to separate the P300 brainwave from background noise, was explored by Serby et al. (2005). The experiment was conducted by allowing the subject to communicate one of 36 symbols in a 6 by 6 matrix. The performance of the system was enhanced by the maintenance of a low error rate throughout the study. Bugli and Lambert (2007) showed that ICA presents a more efficient means for data representation in EEG. ICA often acts as a means of artefact identification (Chiappa, Barber 2006) and to resolve differences in evoked potential in EEG (Onton et al. 2006). It should be noted that various modalities of ICA may be used according to the feature extraction and signal source.

2.5.1.1 PCA as a pre-processing step to ICA

PCA presents an attractive method of data reduction and ICA a means of source extraction (Stone 2004). PCA is preferentially used in a statistical framework, whereas ICA is more commonly employed in data analysis and array processing in recovering unobserved signals (Bugli, Lambert 2007). High classification accuracies of up to 100% have been obtained (Hoffmann et al. 2008).

The validity of using PCA as a pre-processing procedure to ICA is discussed by Attias and Schreiner (1998). Researchers in Japan revealed an increased overall performance improvement of 22.2% in their experimental results using a combination of PCA and ICA processing techniques to help classify EEG patterns. Their experiments used mental imagery tasks for EEG recordings followed by the analysis (Hoya et al. 2003).

The Swartz Center for Computational Neuroscience (SCCN) suggests using PCA to reduce the number of datasets for ICA to extract the information from. This improves the overall computational efficiency of the processing (Delorme, Makeig 2007).

A study conducted by Johnson et al. (2001) using a 64-channel Geodesic Sensor Net (GSN) to record event-related visual-evoked potentials (VEPs) from infants suggests using PCA for data reduction prior to ICA and to increase the ratio of inputs relative to virtual channels – ultimately enhancing the ICA. After PCA data reduction the new data still accounted for 94% of the variance. This method of signal processing has yet been implemented in a multi-class auditory P300 BCI towards FES implementation.

Table 2.2 summarises the use of PCA and ICA in BCIs.

Table 2.2 PCA, ICA and a combination of PCA and ICA signal processing techniques explored in the literature.

<table>
<tr><th rowspan="2">PCA</th><th rowspan="2">ICA</th><th colspan="2">PCA and ICA</th></tr>
<tr><th>Mental imagery</th><th>VEP (ERP)</th></tr>
<tr><td rowspan="2">Vallabhaneni et al. (2004)</td><td>Bugli & Lambert (2007)</td><td rowspan="4">Hoya et al. (2003)</td><td rowspan="4">Johnson et al. (2001)</td></tr>
<tr><td>Serby et al. (2005)</td></tr>
<tr><td rowspan="2">Vinther et al. (2002)</td><td>Erfanian et al. (2004)</td></tr>
<tr><td>Hill et al. (2004)</td></tr>
</table>

2.5.1.2 Temporal and Spatial Manipulation

Xu et al. (2004) used algorithms based on ICA for P300 detection by means of anatomical and psychological knowledge of P300 spatio-temporal progression. PCA and filtering techniques were used to pre-process the EEG signal before ICA to increase its computational efficiency and robustness on a 64-channel system. A reference P300 waveform can be used as a constraint to separate and localise auditory and visual stimuli. The proposed methodology was tested on schizophrenia patients (Spyrou, Sanei & Sumich 2005). Pictorial and 'yes or no' paradigms were shown to produce a high correct response rate as visual stimuli (Neshige et al. 2007) by presenting subjects with a binary output. This analytical method is farther enhanced by a study conducted by Katayama and Polich (1999) which revealed the P300 amplitude and latency of a visual stimulus to be greater than that of an auditory stimulus, hence indicating the lower S/N ratio of auditory P300s versus visual P300s. Both modalities had identical scalp topographies.

2.6 Summary

The advantages and disadvantages of previous BCI systems is summarised in Table 2.3.

Table 2.3 Comparison of different BCI devices.

Type of device	**Problem**	
Mental imagery (SMR and SCP) e.g. (Nijboer et al. 2007, Pfurtscheller et al. 2005)	Disadvantage	• Extensive training time per subject • EEG signal contamination (motor area)
	Advantage	• No external stimulus required
Visual P300 e.g. (Middendorf et al. 2000, Polikoff, Bunnell & Borkowski Jr 1995)	Disadvantage	• Requires a visual stimulus
	Advantage	• Consistent accuracy • No training required
Auditory P300 e.g. (Hill et al. 2005, Pham et al. 2005)	Disadvantage	• Low S/N ratio
	Advantage	• Better for ALS patients • Doesn't require visual stimulus
Multi-class Visual P300 e.g. (Ma, Gao 2008)	Disadvantage	• Requires visual stimulus • FES feasibility unknown
	Advantage	• Multiple degrees-of-freedom
Multi-class Auditory P300 e.g. (Hőhne et al.	Disadvantage	• FES feasibility unknown

2010, Schreuder, Blankertz & Tangermann 2010)	Advantage	• Multiple degrees-of-freedom

Many current FES-BCI systems use mental imagery or visual input as a control signal, however these control signals can be affected by neural degenerative diseases (such as CLIS) and task distraction. Hence systems that employ auditory stimuli as a command interface or control signal present a viable alternative. A robust waveform, such as the P300, requires no training (unlike mental imagery waveforms) and provides degrees-of-freedom if multi-class paradigms are adopted. Various analysis techniques have been used to extract and process EEG recordings. A method using a combination of PCA and ICA techniques (employed by Hill et al. (2005) on an auditory BCI) proves to be effective in processing EEG data. This technique is to be explored on auditory-generated P300s – the computational efficiency of which is of the utmost importance if it is to be used for FES. The data can also be spatio-temporally manipulated in the single-trial scenario to highlight and enhance P300 waveforms (as employed by Xu et al. (2004)). All these contribute to the factors required for effective FES control (refer to section 1.3).

In the light of the above, this thesis will investigate an auditory P300 BCI as a step towards FES application. An investigation into a combination of PCA (for data reduction) and ICA (for P300 extraction) signal processing techniques will be used together with spatially and temporally manipulating the data based on a priori knowledge of the auditory P300 (as per the methodology employed by Xu et al. (2004)). A comparison will be made between auditory and visual accuracies tested on a binary equal-probability (based on the traditional) and multi-class P300 paradigm (employing principles of the multi-class paradigms adopted by Sellers et al. (2006), Schreuder et al. (2010), and Hőhne et al. (2010)) and the signal processing classification accuracy will be compared with no signal processing, PCA alone, and a combination of PCA and ICA with no temporal and spatial manipulation.

The ultimate goal is to create a BCI that is fast, accurate and doesn't impose on real-life situations, but the very existence of the systems are far more important for users.

3 Materials and Methods

This chapter describes the experimental setup materials and procedures, and the methodology required for creating an offline auditory P300 BCI using PCA and ICA techniques (with spatial and temporal manipulation of the P300) as a step towards potential FES application.

The objectives of this chapter are to:

- Describe the experimental paradigm including a proposed multi-class (or selectivity) technique.
- Investigate the method of feature extraction using the signal processing techniques of PCA and ICA.
- Describe the method of spatio-temporally manipulating the data so as to highlight the P300.
- Determine the optimal features for classification using Thornton's (Geometric) Separability Index (GSI).
- Perform the classification using a SVM.
- Describe the cross-validation of data and the calculation of the accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) scores.

3.1 The Experimental Paradigm

The experience of clinical groups utilising BCIs are that different paradigms are successful to varying degrees with different patients. Traditional P300 paradigms consist generally of standard stimuli (S) and a stimulus target (T) experimental technique, whereby by decreasing the probability of one stimulus (i.e.

T) alternately increases the probability of it being distinguished from the other stimuli (i.e. S). These changes in the P300 waveform help BCIs to differentiate between targets and non-target stimuli. For comparative purposes, the investigation compared visual and auditory stimuli and to determine whether the auditory scenario was accurate enough to be utilised in a 'real' environment.

The aim of this research also involved investigating increasing user functionality (or degrees-of-freedom) of alternative paradigms associated with the P300 but also applicable in a 'real' environment. By understanding the factors influencing P300 production and its detection, a more functionally practical paradigm is proposed by combining the relative efficiency that the P300 may be detected with the 'real' practicality of allowing multiple-selectivity.

3.1.1 Materials and Participants

In order to simulate a 'real' environment, it was decided that the use of regular earphones should be utilised for the auditory stimulus. Electrical noise generation was taken into consideration due to the proximity of the earphones to the high resolution 128-channel GSN. The earphones used and the specifications thereof can be seen in Figure 3.1 and Table 3.1.

Figure 3.1 Philips In-ear Noise Isolation Headphones used for the auditory experiments (Philips 2011).

Table 3.1 Philips In-ear Headphones specifications used in the auditory experiments (Philips 2011).

Specification	**Value**
Impedance	16 Ω
Frequency Range	6 Hz to 23.5 kHz
Sensitivity	102 dB
Maximum Power Input	50 mW
Connectors	3.5 mm Stereo Mini Plug

The visual stimulus was produced by a PC on a high frequency and resolution (120 Hz vertical refresh rate) CRT monitor so as to reduce the artefacts produced by 'flicker' on the display. The subjects were seated 55cm from the screen (using a chin rest) so as to maintain uniformity (standard height and distance) throughout the recordings. The experimental setup is shown in Figure 3.2.

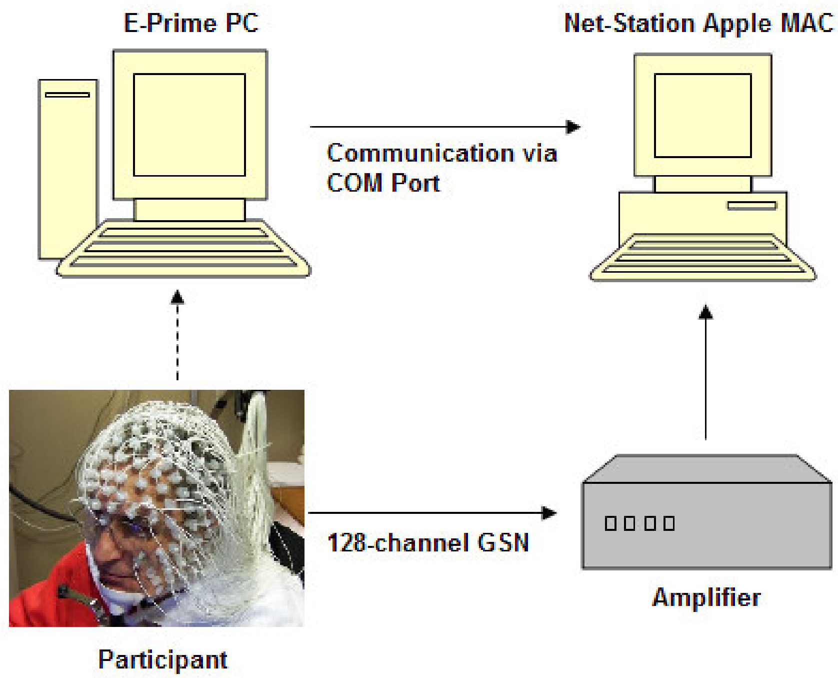

Figure 3.2 Diagram showing the GSN recording system setup.

The data was gathered using the 128-channel GSN EEG device[13] (Electrical Geodesics 2001). See Appendix F for the specification of this device. E-prime (Physiology Software Tools) was used to present the tasks to the subject and also to communicate with Net-Station (Electrical Geodesics) by sending event signals when stimuli were produced. Appendix G illustrates an example of the program developed in E-prime to present the subjects with each experimental paradigm. Net-Station is the software associated with the GSN to record and stores the EEG signals. Figure 3.3 shows the GSN net and Figure 3.4 is an example of the data acquisition configuration.

[13] Sample rate = 200Hz; Resolution = 16 bits; Nominal Gain = 1000.

Figure 3.3 The Geodesic Sensor Net (GSN) device (Electrical Geodesics 2001).

Figure 3.4 An example of the data acquisition configuration (Electrical Geodesics 2001).

Five experiments of 180 trials each were to be conducted on 15 subjects (right-handed males between the ages of 21 and 30) using the high resolution system. Subjects were asked to wash their hair with shampoo to ensure good conductivity during the recording process. No disabled subjects were used in the experimentation, but the experiment was setup so as to simulate a subject suffering from CLIS (no movement) and other neurological/spinal disorders (limited movement). All subjects signed consent forms and were paid for their participation. The International Federation of Clinical Neurophysiology (IFCN) EEG recording standards is a standard that is commonly adopted in clinical EEG recording (Nuwer et al. 1999). The standard requires that certain conditions be met e.g. the subject's medical history and time of recording. An attempt was made to satisfy the conditions stipulated by this standard so as to obtain better quality EEG (although this is not a requirement for research based EEG). Attempts were made to eliminate (or at least mitigate) all sources of potential noise or artefact production. A self-report was conducted to assess the current health status of the subject, vision and hearing abnormalities, medication, food and alcohol consumption, known neurological disorders and general well-being. Most recordings took place during the same time of the day, within the same season of the year, and with all variables as standard as possible. An example of the pre-recording questionnaire can be found in Appendix H. The experiment has been approved by the University of Cape Town Health Sciences Faculty Human Ethics Committee (REF: 449/2007); the letter of approval is in Appendix I. The subject consent form used is in Appendix J.

3.1.2 Choice of Tasks

To explore the efficacy of visual versus auditory stimuli, five experiments were conducted per subject. Before each experiment the recording was validated by observing the EEG with eyes open and eyes closed. It is well documented in literature that 'eyes closed' EEG has the characteristic of an increase in the alpha amplitude at the occipital channels (Srinivasan 1999).

The five paradigms included visual and auditory stimuli, a requirement for a button to be pushed in certain instances, and a binary equal-probability P300 approach (based on the traditional approach). The use of three stimuli of equal probability is assessed for classification accuracy and efficacy so as to simulate multiple decision processes in actual scenarios. It was decided to utilise three different stimuli in an attempt to add extra selective functionality for the user (as opposed to the traditional paradigm utilising only two differing stimuli). The five experiments are summarised in Table 3.2.

Table 3.2 Five experimental paradigms per subject. S_1S_2T = $Stimulus_1$-$Stimulus_2$-Target (i.e. 2 non-target stimuli and 1 target stimulus) and S_1T = $Stimulus_1$-Target (i.e. 1 non-target stimulus and 1 target) as per Polich and Criado (2006).

Task	Stimulus	Method of Identifying Stimuli	Description of Stimuli	Duration of Task
1	auditory (S_1S_2T)	count	Three 1 second tones of different frequencies (500 Hz, 1500 Hz, 3500 Hz)	2.5 s X 180 trials = 7 min
2	auditory (S_1S_2T)	button push	Three 1 second tones of different frequencies (500 Hz, 1500 Hz, 3500 Hz)	2.5 s X 180 trials = 7 min
3	visual (S_1S_2T)	count	Three directional arrows (up, left, right) appearing for 1 second	2.5 s X 180 trials = 7 min
4	visual (S_1S_2T)	button push	Three directional arrows (up, left, right) appearing for 1 second	2.5 s X 180 trials = 7 min
5	auditory (S_1T)	button push	Two 1 second tones of different frequencies (500 Hz, 3500 Hz)	2.5 s X 180 trials = 7 min
	visual (S_1T)	button push	Two directional arrows (up, down) appearing for 1 second	2.5 s X 180 trials = 7 min

The experimental setup included a stimulus type (auditory or visual) and a target identification method (button pushing or silent counting). The sensory modality for the chosen stimulus was either a frequency-dependent sine wave tone or a visible directional arrow. 180 trials were used in each sub-experiment. This was the maximum number of repetitions to be collected per individual before fatigue adversely affected P300 generation amplitude (refer to Appendix G for fatigue ratings). The target stimulus for each sub-experiment was randomly chosen for the subject to avoid any bias towards ease of recognition. In the multi-class paradigm, the percentage of target versus non-target stimuli over the period of 180 trials was exactly 33.3% (or $\frac{1}{3}$) i.e. the chosen target of the three stimuli served as the target in $\frac{1}{3}$ (i.e. 60) of the trials. Thus, in representing a possible scenario where a user has three selectivity options, there is no probability bias towards any one potential target. Two forms of target identification were utilised in order to replicate a user with CLIS (silent counting, with the count being verified post each experiment[14] – refer to Appendix K) and one with limited movement (button pushing)[15]. Additionally, during analysis for the proposed algorithm, the button pushing aided the identification of the target P300. Those experiments where silent counting was utilised meant the subject had to reveal the target stimulus post each experiment (because the target was randomly chosen for each subject by the E-prime program).

Each of the five experiments included:

- Presenting the subject with a mono auditory target stimulus amongst two other stimuli (subjects were instructed to count the total number of target stimuli);

[14] P300 amplitude is directly proportional to attention. Verification of the count would indicate attention to the experimental paradigm.
[15] It should be noted that button pushing generates smaller P300 amplitudes and is hence not the preferred target identification technique (Salisbury et al. 2001).

- The same procedure as experiment 1 except that a button was pushed to indicate a target and a separate button was pushed to indicate a non-target[16];

- Presenting the subject with a visual target stimulus amongst two other stimuli (subjects were instructed to count the total number of target stimuli);

- The same procedure as experiment 3 except that a button was pushed to indicate a target and a separate button was pushed to indicate a non-target;

- A binary equal-probability P300 experiment consisting of either an auditory or visual stimuli in the single-stimulus (ST) paradigm.

The binary equal-probability paradigm consisted of two stimuli of equal probability in random sequence batches. The target was presented to the subject prior to the experiment (hence the other stimulus was considered the non-target or standard stimulus). Although the traditional paradigm recommends decreasing the probability of the target stimulus in order to enhance the P300 generation (refer to Appendix D), an attempt was made at simulating a 'real' asynchronous paradigm where the user's choice of target is not pre-defined by the experimental setup. The same approach was adopted for the three-stimulus paradigm[17].

The choice of an auditory or visual stimulus for the binary equal-probability paradigm (hereafter referred to as the traditional paradigm) alternated per subject

[16] Buttons are pushed for target and non-target stimuli so as to minimise the variation between stimuli and maintain the integrity of the P300. This method is discussed in Luck (2005) and Burkard et al. (2007).
[17] The traditional three-stimulus paradigm consists of an infrequent non-target, standard stimuli and the target stimulus.

to reduce subject fatigue. Participants noted that their interest and concentration decreased with time and a decision was made prior to recording to only include one binary equal-probability experiment per subject for comparative purposes. Note: hereafter, when referring to the experimental *binary equal-probability* paradigm, *traditional* paradigm will simply be utilised in the succeeding chapters.

In each case the subject was familiarised with the target beforehand and allowed to practice. The procedure for each experiment was displayed on the screen prior to recording. In order to reduce eye movement artefact, subjects were required to focus on a cross-hair in the middle of the screen (see Figure 3.5) for both visual and auditory experiments so that the only variables that changed between the recordings were the stimuli. Participants were also informed to sit still and not to move during the recording so as to minimise artefact production and muscle contractions due to the sensitivity of the GSN and the resultant EEG recording.

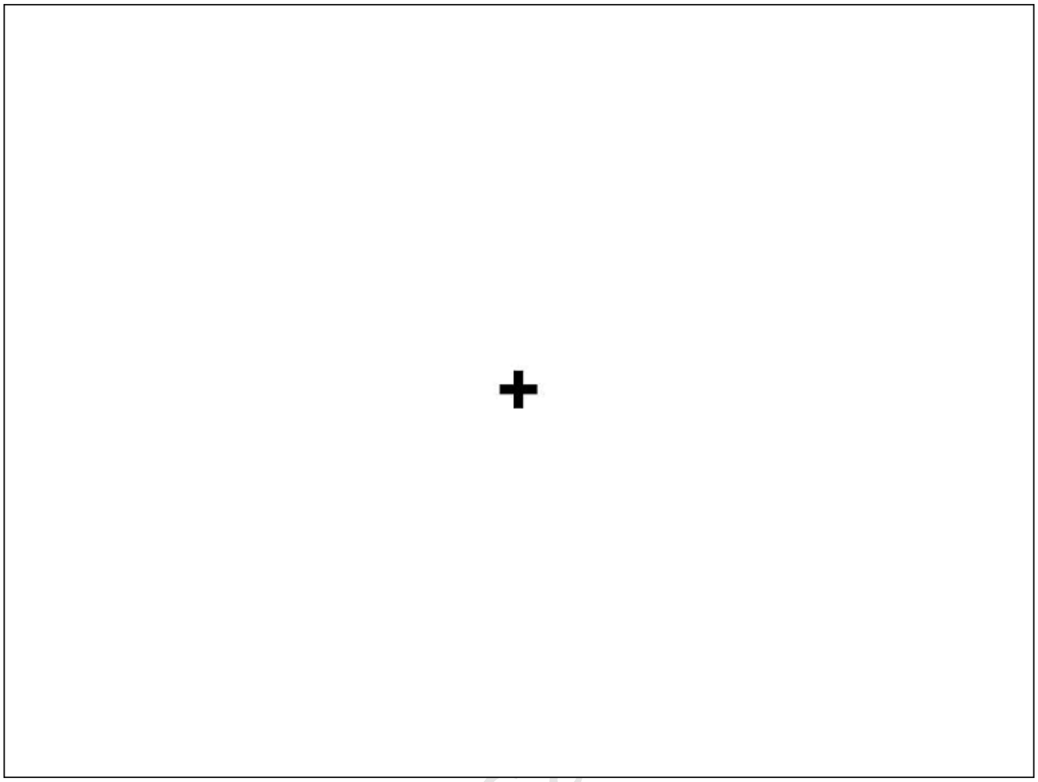

Figure 3.5 Example of the cross-hair that participants were required to focus on during each experiment (colours have been inverted).

Auditory stimuli varied only by frequency (volume and length of tone were kept constant throughout). The predetermined sinusoidal tones had frequencies of 500 Hz, 1500 Hz, and 3500 Hz, which presented the least level of discomfort. These were chosen after subjects (in preliminary studies) indicated from a variety of frequencies which three provided the best discernible differences from a selective range.

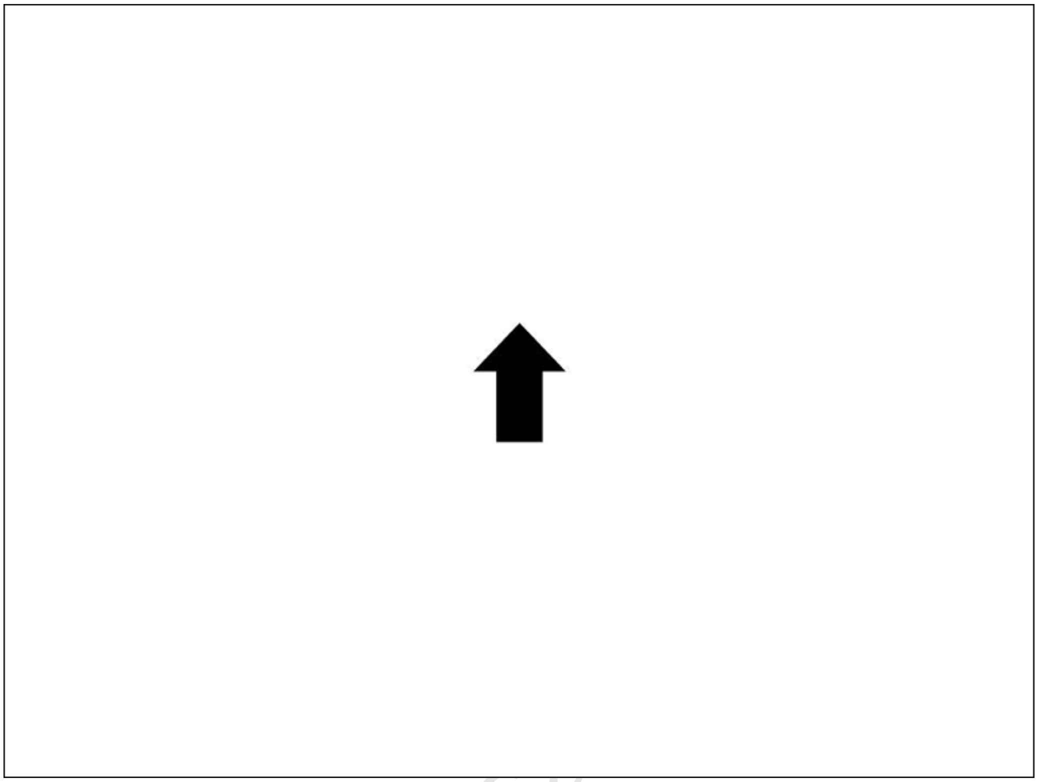

Figure 3.6 For the visual stimulus experiments, the cross-hair would change briefly to a random arrow direction for a period and then change back to the cross-hair (colours have been inverted).

Visual stimuli consisted of three arrows of equal size and positioning which only varied by orientation – left, right, and up (and down in the traditional paradigm). See Figure 3.6 for an example of the visual stimulus. The target in each case was randomly selected for cross-validation averaging. In instances 1 and 3 the subjects were required to count the number of targets in their heads and in instances 2, 4 and 5 they were required to push a button. The paradigms were established according to the ERP technique summarised in

Table 3.3 and sampled at 200 Hz. There was a 1.5 second delay between each 1 second stimulus due to the latency of the waveform and to allow the P300 potential to attenuate before the next stimulus. Decreasing the time period between stimuli would alternately increase the task difficulty. Increased task difficulty affects the production of the P300 waveform (Kok 2001). See Figure 3.7 for an example of the experimental timeline.

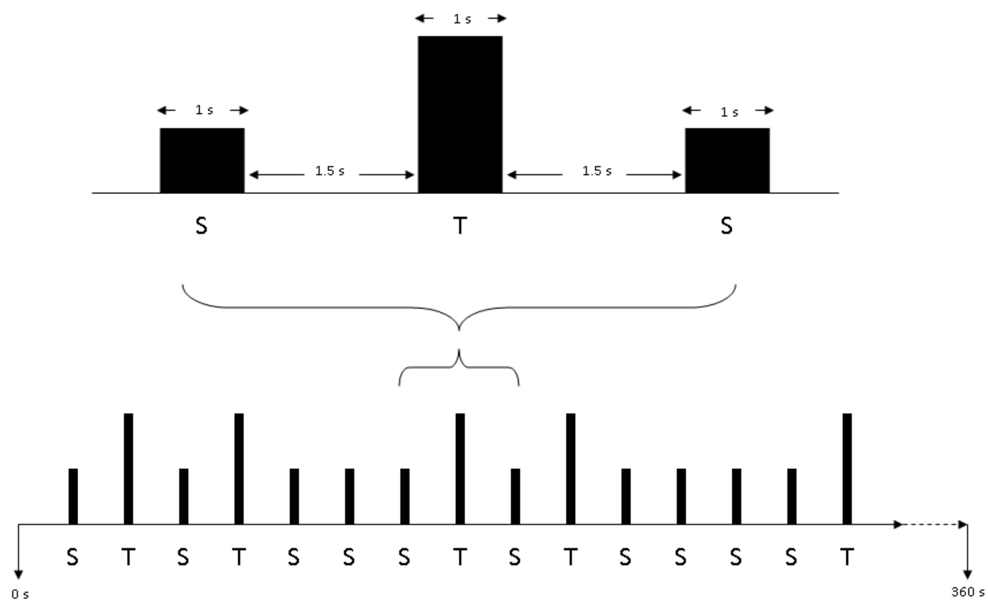

Figure 3.7 Experimental timeline.

Table 3.3 Rules and Strategies for ERP testing (modified from Luck (2005)).

	Rule or Strategy
1	Avoid physical stimulus confounds (vary only psychological conditions)
2	Use the same number of trials for comparisons
3	Be cautious when the presence or timing of motor responses differ between conditions
4	Vary experimental conditions within trial blocks and not between trial blocks
5	Don't assume amplitude and latency are linearly related to a cognitive process
6	Focus on a specific component
7	Use well studied experimental manipulations
8	Isolate components with different waves
9	Focus on components that are easily isolated
10	Use component independent experimental designs if possible
11	Hijack useful components from other domains

Fatigue and concentration affect P300 production and hence a compromise was made between the number of trials[18] and fatigue[19] or concentration[20].

[18] The greater the number of trials the easier it is to extract the P300 waveform from the noise by averaging (Nicolaou, Nasuto & Georgiou 2008).
[19] The more fatigued a subject, the more attenuated the P300 waveform (Massar et al. 2010).
[20] Increased concentration improves P300 detection (Dal Seno, Matteucci & Mainardi 2010).

3.1.3 Summary of Testing Protocol and Conditions

All experimental datasets were collected from predominantly right-handed male subjects over the age of 21 by the author using the high resolution 128-channel Geodesic Sensor Net (Electrical Geodesics 2001) device and the associated Net-Station (Electrical Geodesics) software.

An average of 10 separate cross-validation sets was used to determine the prediction accuracies. Sensitivity, specificity, PPV and NPV scores were also calculated for these results. Every effort was made to standardise the test conditions. The time of day, position of the screen, and volume of the tones were kept constant throughout the process. Subjects were also asked a series of questions relating to their diet, medical condition, and fatigue (see Appendix F). The order of testing was kept the same for all 15 subjects. Factors such as fatigue and concentration had to be taken into account when assessing the results. Subjects were asked to report their level of fatigue on a scale of 1 to 5 at the end of the experiments (see Appendix G Table G.1). Hence, due to many subjects reporting a high fatigue rating, only one traditional paradigm was chosen for each subject: either visual or auditory stimuli (refer to Table 4.1 to Table 4.4). This included a button push as per the traditional paradigm setup. As many variables as possible were eliminated in testing to ensure the only measurement was as a result of the paradigm chosen.

3.2 Data Analysis

BCI detection systems can (generally) be divided into three main stages as shown in Figure 3.8:

- Pre-processing – continuous EEG data is screened for artefacts, and contaminated data is removed manually (bad channels) or automatically (electrooculogram (EOG) or eye artefacts are subtracted from the EEG). High pass or low pass filters are applied to raw data to remove unwanted frequencies produced by noise prior to screening biological EEG production[21]. The data is then segmented into smaller epochs (sliding window) containing the desired information.

- Feature extraction – EEG data is mapped into an appropriate feature space for classification utilising the signal processing techniques. The feature vectors contain the desired information upon which the tasks are based.

- Classification – the extracted features are classified into different classes. Specificity, sensitivity, PPV and NPV scores are also calculated in order to show the degree of confidence of the classification accuracy.

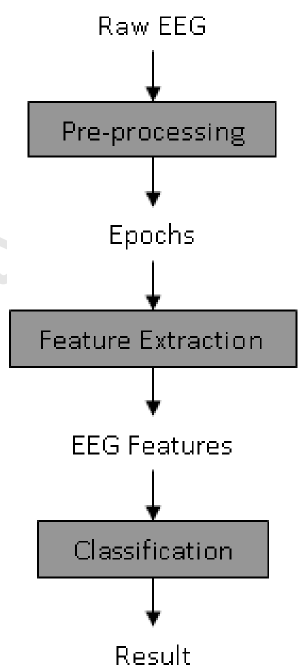

Figure 3.8 Diagram showing the different elements of data analysis in a mental task algorithm.

[21] A notch filter is used to remove unwanted electrical noise at 50 Hz.

Each stage of the data analysis for this research is shown in Figure 3.9 and is discussed in the succeeding sections.

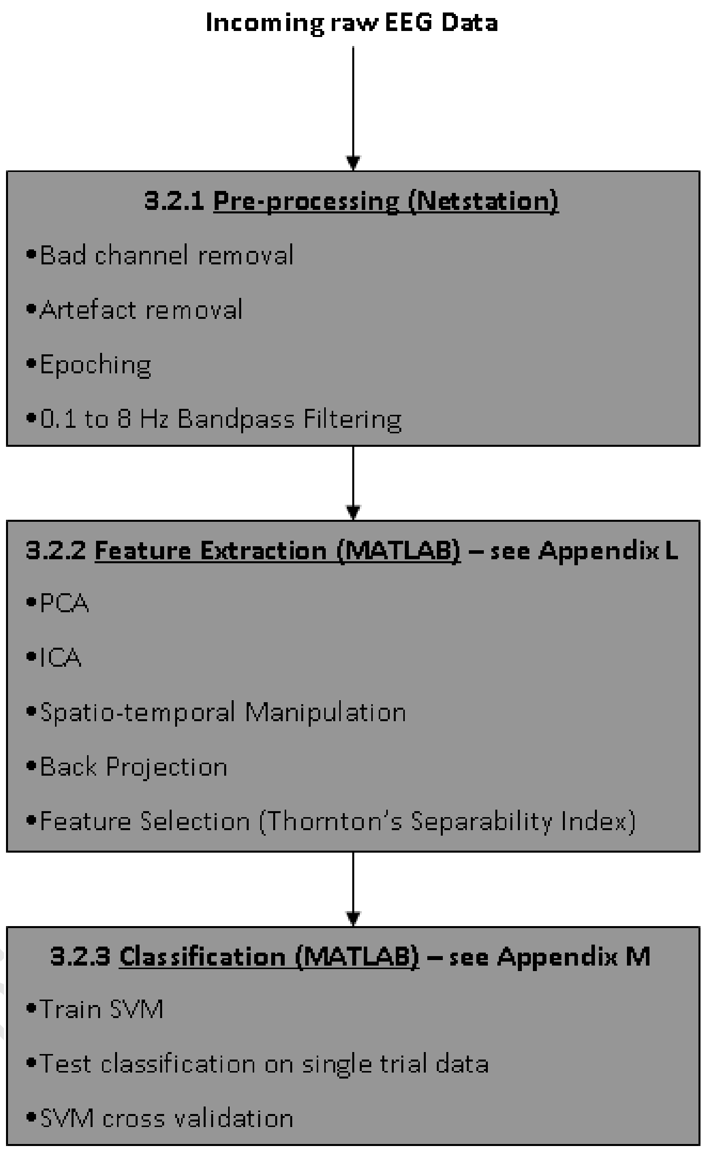

Figure 3.9 Diagram showing the data analysis procedure.

3.2.1 Pre-processing

The recorded signal was pre-processed using a combination of Net-Station (Electrical Geodesics) techniques and EEGLAB[22] (Delorme, Makeig 2004). Net-Station contains embedded algorithms to perform filtering, artefact removal, and epoching. The system uses the vertex (channel 129 or Cz) as a 'reference' electrode; and therefore each channel records the potential between the recording electrode and the vertex. Certain channels were discarded (refer to Appendix L section L.7) primarily due to the fact that they give rise to noisy data[23], but also because they were not in the region of interest. Figure 3.10 shows the electrode locations of all 128 channels (and the 'reference' channel Cz).

[22] MATLAB embedded software dedicated for EEG analysis.
[23] Any muscle movement in the face or neck significantly distorts the data recorded at those sites.

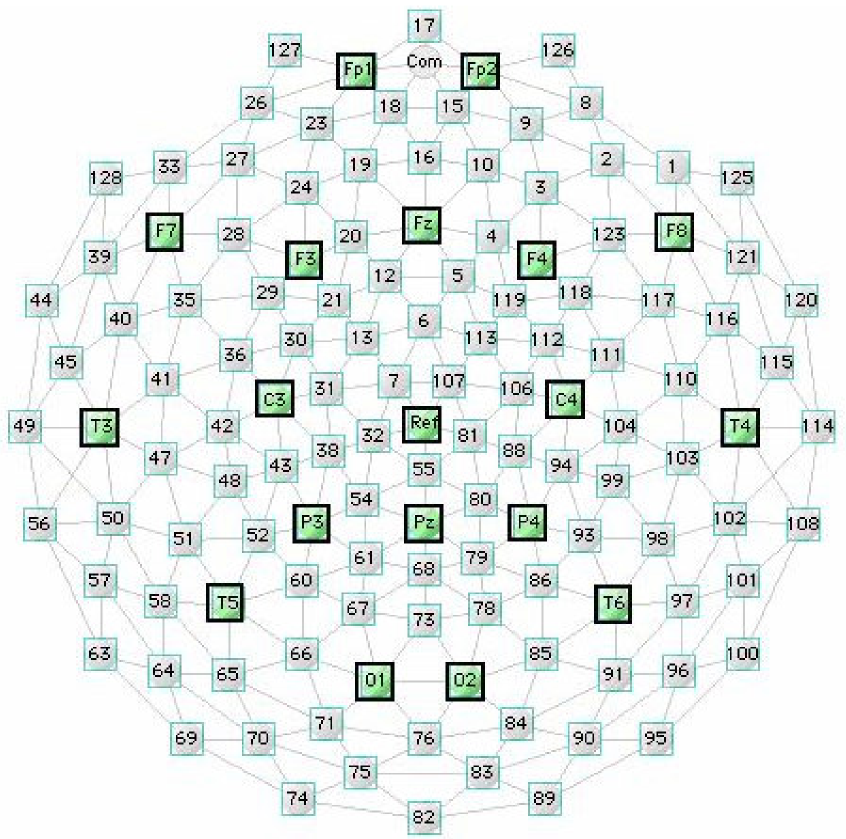

Figure 3.10 Electrode locations for 128-channel Geodesic Sensor Net system using the 10-20 International system of electrode placement. Ref (channel) = Cz.

A 50 Hz notch filter was used to remove electrical noise and a 0.01 Hz to 33 Hz Bessel filter was used to monitor the recorded EEG while removing unwanted frequencies during the recording. Additionally eye artefacts (EOG subtraction) and other bad channels were removed (by visual inspection) from the recordings in Net-Station and the data was then converted to raw format to be loaded into MATLAB. After being exported to MATLAB, the ‘cleaned’ EEG data was referenced to the right mastoid, segmented into 650 ms epochs[24] (starting at the time of the event or

[24] These are time-locked EEG segments of equal lengths at specific times relating to the time of the event. Epochs can be averaged in some instances to improve the S/N ratio before feature extraction (Thulasidas, Guan & Wu 2006).

stimulus – see Figure 3.11) in each channel and 0.1 Hz to 8 Hz band-pass filtered (spectrum analysis reveals that the principal energy of the P300 is in the 1 to 8 Hz band (Xu et al. 2004), but using high-pass filtering above 0.1 Hz tends to attenuate the P300 waveform).

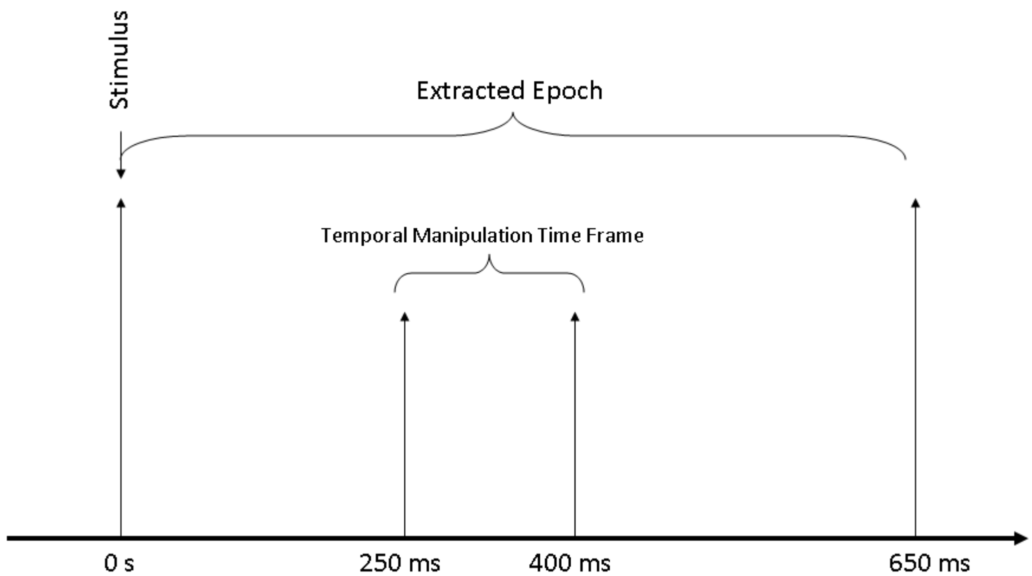

Figure 3.11 Timeline of the extracted epoch from the time of stimulus (T or S) presentation. The temporal manipulation timeframe (refer to section 3.2.1.3) can also be seen within this epoch.

3.2.2 Feature Extraction

In order to optimise classification of target and non-target (or standard stimuli) P300s, certain features from recorded data need to be extracted. As is the case in EEG, when data is too large to process and is redundant[25] then the input data should be reduced into a representative set of features i.e. feature extraction (Lugger et al. (1998) and Kaplan and Shishkin (2000)). In EEG, feature extraction is

[25] There is much data, but not much information.

the mapping of epochs into a feature vector space that is suitable for classification. This process is an integral part of BCI systems as it reduces the amount of processing resources required to represent complex EEG data accurately, and also simplifies the task of discriminating between pattern classes of the original signal. If the features are chosen carefully the newly derived feature set will extract the relevant information from the EEG in a reduced representation[26]. Classification is then simplified. Overlapping information should be avoided as unnecessary information may confuse the classifier or over determine the problem (Mohamed 2004).

The choice of the optimal feature extraction method is dependent on the subject, the mental activity to be detected, and the requirements specific to the system's functionality. The purpose of the feature extraction process in BCI systems is to extract EEG features that (optimally) encode the user's message[27]. In most instances the extracted features are of a lower dimensionality than the original signal (Wolpaw et al. 2002). It is important to ensure that BCI features are not contaminated with artefacts, as sometimes artefact signals may correlate with the user's intent, and be incorrectly selected as signal features. Thus pre-processing the signal for artefact reduction is of the utmost importance.

3.2.2.1 Principal and Independent Component Analysis

The different signal processing techniques could now be employed on the data i.e. PCA, a combination of PCA and ICA, and spatio-temporal manipulation thereof. A full explanation of the theory and mathematics behind PCA and ICA is discussed in Appendix N. The combination of PCA for data reduction was used together with ICA to formulate an independent component (IC) matrix from the

[26] Unreliable classification occurs when not enough information is captured in the selected features.
[27] In this case, the P300 reflects the user's message.

training data in MATLAB. This forms part of the first step in P300 feature extraction in the proposed algorithm. Selection of the features and number of principal and independent components for training and classification is discussed in section 3.2.2.4. A test was carried out on a subset of the data to determine the optimal number of components to retain until the incremental accuracies became negligible. An assumption can be made that these components then contained the most variance (and therefore information). The same procedure was carried out for both PCA and the combination of PCA and ICA.

With regards to the spatio-temporal manipulation, the calculated IC matrix could now act as an 'unmixing' matrix (W) for single-trial data. The ICs of each single-trial epoch were then manipulated to highlight the qualities associated with P300 detection. The channel set and timeband were predetermined based on the characteristics of a P300 waveform. The final step involved the manipulated data being multiplied by the pseudo-inverse of the 'unmixing' matrix to obtain spatio-temporally enhanced data according to the ICs representing the P300 wave. This new matrix portrays the contributions from each channel to the P300 according to its temporal and spatial properties. A process flow of the data analysis that was adopted is shown in Figure 3.12.

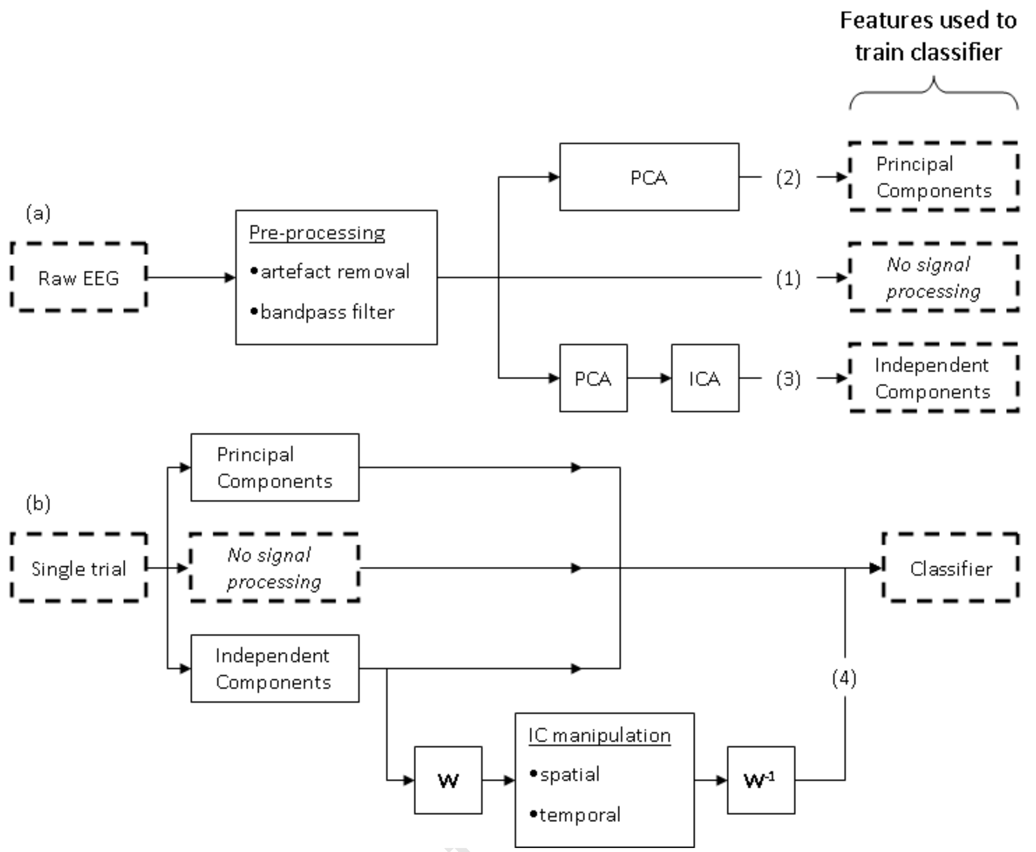

Figure 3.12 Algorithm for P300 detection: (a) training (see Appendix L section L.1 to L.4, and L.8) and (b) testing phase (see Appendix L section L.5 to L.7). The four signal processing techniques are labeled (1) to (4).

A comparative analysis was conducted using only Varimax PCA rotations against the proposed Varimax PCA Infomax ICA combination. Varimax and Infomax relate to different rotations of the data. An explanation of the theory surrounding Varimax and Infomax rotations of data is discussed in Dien et al. (2007). After the PCA Infomax ICA decomposition, the spatial and temporal manipulations of the ICs (in time and space domains) are performed and discussed in section 3.2.2.2.

PCA and ICA algorithms in EEGLAB are used to perform the signal processing of the data. The software uses Infomax ICA which is based on stochastic gradient learning rules. The algorithm “explicitly tries to maximise the joint entropy of a nonlinear function of the separated outputs; however, it implicitly minimises the mutual information between the separated outputs so as to make them mutually independent” (Langlois, Chartier & Gosselin 2010).

3.2.2.2 Temporal and Spatial Manipulation of Data

Temporal manipulation of data considers the features of the ICs relating to the time domain to decide whether they should be kept or not. The latency and amplitude of the waveform are used to manipulate the components. Those ICs with relatively larger amplitude in the latency range of the P300 were kept, while the others were set to 0. The latency range (within the 650 ms epochs) for the captured data was set from 250 ms to 400 ms as determined by the averaged ERP data (refer to Figure 3.11 and Appendix O). Refer to Appendix L sections L.5, L.6, and L.7 for the MATLAB code used to perform the spatio-temporal manipulation.

Spatial manipulation uses *a priori* knowledge of the physiological properties of the P300 to determine whether the components are kept or not dependent on the spatial distribution of the ICs. The method used is as follows. Denote W^{-1} (the inverse of matrix W) as:

$$W^{-1} = \begin{bmatrix} w'_{11} & \cdots & w'_{1j} & \cdots & w'_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ w'_{i1} & \cdots & w'_{ij} & \cdots & w'_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ w'_{n1} & \cdots & w'_{nj} & \cdots & w'_{nn} \end{bmatrix} \tag{1}$$

and

$$u = \begin{bmatrix} u_1(t) \\ \vdots \\ u_j(t) \\ \vdots \\ u_n(t) \end{bmatrix}. \tag{2}$$

Thus the linearly mixed n observed signals $x = [x_1, x_2, \ldots, x_n] = W^{-1}u$, where u may be considered the estimation of the n unknown independent sources $s = [s_1, s_2, \ldots, s_n]$.

The jth column of W^{-1} reflects the intensity distribution of each electrode of the jth IC u_j (Xu et al. 2004). We transform the spatial pattern matrix W^{-1} into an intensity order matrix M with the same dimension. The value of the element m_{ij} in M is set to be the order number of the value $w_{ij}^{'}$ in the corresponding column vector of W^{-1}. For example, if $w_{ij}^{'}$ is the largest element in column j, then $m_{ij} = 1$. And likewise if $w_{ij}^{'}$ is the second largest element in column j, then $m_{ij} = 2$.

Following from this a spatial distribution matrix Q representing an electrode set relating to the brain activities associated with the P300 is chosen (refer to Appendix L section L.7). $Q = \{q_k\}$, where q_k is the index number of electrodes and is equal to the row index of the multichannel EEG matrix x. For P300 potential extraction the electrodes selected should include the parietal region[28], because prior knowledge indicates that this is where it is most prominent. The rule of spatial manipulation of ICs is given by:

$$u_j^* = \begin{cases} u_j & \exists q_k \in Q, \quad m_{q_k j} \le T \\ 0, & else \end{cases}, \tag{3}$$

where T is the threshold of order of admission. For example, set $T = 1$, then only the ICs satisfying the condition that the electrode corresponding to the largest element of the spatial pattern belongs to the set, and if $T = 2$, then the ICs corresponding to the two largest elements that belong to the set are retained, and

[28] The corresponding electrodes Pz, P1, and P2 are situated near the vertex.

so on. In other words, T is introduced to keep the most prominent spatial information relating to the P300. Finally after this manipulation u^{*} holds most of the source information about the P300, and all other elements are set to 0 (Xu et al. 2004).

3.2.2.3 Back Projection

After the temporal and spatial manipulations of the ICs, the vector of the manipulated components $u^{'}$ was back projected to scalp EEG to obtain the scalp distribution of the P300 potential:

$$x^{'} = W^{-1}u^{'}, \tag{4}$$

where $x^{'}$ is the P300 enhanced EEG for feature extraction.

3.2.2.4 Feature Extraction

Initial selection of signal features may be based on standard guidelines from known locations and temporal and spectral characteristics of EEG supplemented by operator inspection of initial topographical and spectral data from each user (Wolpaw et al. 2002). These methods can also be replaced by automated feature selection methods. Thornton's (Geometric) Separablity Index (GSI) presents an effective (and heuristic) means of selecting features for classification.

GSI is defined as "the fraction of data points whose classification labels are the same as those of their nearest neighbours. Thus it is a measure of the degree to which inputs associated with the same output tend to cluster together" (Anthony, Ruther 2011). Thus for a given task f (target function), it is the fraction of data whose nearest neighbour shares the same output class (Thornton 1997).

$$GSI(f) = \frac{\sum_{i=1}^{n} f(x_i) + f(x_i^{'}) + 1 \bmod 2}{n}, \tag{5}$$

where x = data set; $x_i^{'}$ = nearest neighbour of x_i; and n = total number of data.

The GSI has a value of between 0 and 1, with 1 indicating a complete geometric separability between the two classes of data points, and 0.5 indicating a random distribution of points. The case of 0 GSI is extremely uncommon, as it only happens when the data points are arranged like a chessboard i.e. where each point's nearest neighbour belongs to its opposite class (Thornton 1997).

The GSI was computed for the data sets and results compared. The best component (or feature) set using varying combinations of features from the different signal processing techniques was used as the input to the SVM (refer to the code in Appendix L section L.9). Combinations of between 1 and 25 features were calculated for the best GSI for each relevant channel. Features were selected by incrementally calculating the GSI on a subset of test data (650 ms processed target and non-target epochs) to a point where accuracy did not improve (i.e. an asymptotic approach). The feature set showing a higher GSI more frequently was then chosen as the feature inputs to the SVM for classification. An example of the method of choosing this feature set for subject 1 is shown in Appendix L Table L.1. The most prominent feature combination was used on all the data in contrast with calculating the index for each test (increased accuracies can be obtained by calculating individual indices). A generic subset of features was chosen.

3.2.3 Classification

Classification of EEG recordings represents the backbone of decision making BCIs. SVMs, neural networks (NNs), and linear discriminant analysis (LDA) classifiers represent some of the more powerful classification techniques available. These learning algorithms are trained on data to detect class separability.

Once the appropriate features (determined by section 3.2.2.4) were extracted, they were presented to a classifier in order to determine the task. Extant BCIs use a variety of classifiers that measure the membership of a feature vector with respect to each mental activity by means of machine learning approaches. In this case a SVM was used to classify whether or not a feature vector of data from a single trial was the target[29]. An explanation of the theory and mathematics behind SVMs can be found in Appendix P. Training data was used to generate a classification function. Additionally SVMs do not require pre-defined rules to function as a classifier and thus present an attractive means of classifying EEG data due to the high complexity of EEG recordings.

A linear support vector machine (LSVM) is used to classify a moving average of the data from 0 to 650 ms for a single-trial epoch. GSI was used to determine the optimal features for classification.

3.2.3.1 Classification using a linear SVM

A SVM toolbox (Gunn 1998) was used to classify the EEG data in MATLAB, using a linear kernel and C = 10 (determined via results obtained from a test data set run on the classifier – refer to Appendix M section M.2). The linear kernel was chosen due to the high dimensionality of the input feature space; non-linear classifiers were therefore not necessary. The SVM toolbox was validated in Lin (2007).

[29] SVMs have shown to outperform many classification algorithms in many different problems and represents a robust classification technique for the proposed method (Thulasidas, Guan & Wu 2006).

3.2.3.2 SVM cross-validation

Cross-validation allows an estimation of how a model will generalise on unseen data. It is a technique for assessing how the results of a statistical analysis will perform against and independent data set. The leave-one-out cross-validation (LOOCV) technique was used due to relatively limited amount of data.

LOOCV briefly is if (x_k, y_k) represents the kth record, it is temporarily removed from a dataset and the SVM is trained on the remaining information in the dataset. (x_k, y_k) can now be tested by the classifier as the 'unseen' data. This is performed for each record and an average is obtained indicating the accuracy of classification.

For this investigation, 10 cross-validations were conducted on 10 randomly chosen target P300 instances and the LSVM was trained on the remaining datasets. The average accuracy of the cross-validations gives a good approximation of the accuracy of the SVM classification for the recorded experiments on a single-trial basis.

3.2.3.3 Individual Statistical Measures

Accuracy is a measure of the degree of closeness to the actual (or true) value. It is a measure of how well a binary classification test correctly identifies and excludes a condition.

Accuracy was calculated as follows:

$$\frac{TP + TN}{TP + FP + FN + TN}, \tag{6}$$

where TP was the number of true positives, TN was the number of true negatives, FP the number of false positives and FN the number of false negatives.

Scores of 100% indicated perfect classification accuracy and correct identification of all conditions.

Sensitivity and specificity scores give an indication of how good a test (or signal classification in this case) is. They are statistical measures of the performance of a binary classification. Sensitivity measures the proportion of actual positives that are correctly identified i.e. the percentage of correctly identified target P300s. Specificity measures the proportion of negatives which are correctly identified i.e. the percentage of correctly identified non-target P300s.

Sensitivity was calculated as follows:

$$\frac{TP}{TP + FN}. \tag{7}$$

Alternatively specificity was calculated using the following formula:

$$\frac{TN}{TN + FP}. \tag{8}$$

A false positive is also known as a type I error and occurs when a statistical test rejects a true null hypothesis. The rate of the type I error (or false positive) is denoted by alpha (α) and usually equals the significance level of a test. If a test of significance gives a *p*-value lower than α, the null hypothesis is rejected (see section 4.5).

Similarly a false negative is also known as a type II error and occurs when a test fails to reject a false null hypothesis. The rate of the type II error (or false negative) is denoted by beta (β) and is related to the power of a test (1 – β).

Two other measures which operate concurrently with sensitivity and specificity in helping to analyse the prediction accuracies of the classification are the positive predictive value (PPV) and the negative predictive value (NPV). The PPV is the proportion of positive classifications which are correctly identified as being positive, while conversely the NPV is the proportion of negative classifications which are correctly identified as negative. It is one of the most important measures in a diagnostic process because it reflects the probability of a positive identification of a target and hence the resultant output of the BCI.

PPV was calculated using the formula:

$$\frac{TP}{TP+FP}, \tag{9}$$

while NPV was calculated using:

$$\frac{TN}{FN+TN}. \tag{10}$$

A summary of the relationships among the terms can be seen in Table 3.4.

Table 3.4 Relationships among terms.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Actual Condition</td><td colspan="2" rowspan="2"></td></tr>
<tr><td>Target</td><td>Non-Target</td></tr>
<tr><td rowspan="2">Linear SVM Outcome</td><td>Target</td><td>True Target (TP)</td><td>False Target (FP)</td><td>=TP/(TP+FP)</td><td>PPV</td></tr>
<tr><td>Non-Target</td><td>False Non-Target (FN)</td><td>True Non-Target (TN)</td><td>=TN/(FN+TN)</td><td>NPV</td></tr>
<tr><td colspan="2" rowspan="2"></td><td>=TP/(TP+FN)</td><td>=TN/(FP+TN)</td><td colspan="2" rowspan="2">Accuracy</td></tr>
<tr><td>Sensitivity</td><td>Specificity</td></tr>
</table>

4 Experimental Results

This chapter is divided into five sections. Section 4.1 discusses the testing protocol and conditions. Each of the next three sections is focused around the objectives of this research and the relative accuracies obtained during testing. Each subsection includes the results of the testing, analysis thereof, and draws on some basic conclusions. Section 4.2 is based on the comparison of the experimental paradigms, while section 4.3 focuses on the comparison between the auditory and visual accuracies. Section 4.4 focuses on the accuracies of the different signal processing techniques. The last section summarises the full results as an indication of the feasibility of the proposed solutions.

It was found that the EEG data recorded was similar in most respects for each subject. Differences in aptitude and application were more apparent between individuals for the different experiments. No data was combined or averaged across subjects. Definitions of accuracy, sensitivity, specificity, PPV and NPV can be found in section 3.2.3.3. Group statistics are conducted in section 4.5. The value from the channel showing the highest classification accuracy for each test and subject was chosen for analysis.

4.1 Common characteristics between subject results

Although some differences were found between subject classification results, the similarities included:

- the traditional paradigm proved to produce the most accurate results;
- no accuracy improvement over silent counting was found when utilising the button pushing technique;

- in general, visual stimulus experiments produced better classification accuracies;
- signal processing techniques between subjects generally noted the same proportional improvement or deterioration; and,
- PCA proved the vastly superior signal processing technique for these set of experimental paradigms; and
- the multi-class paradigms did not match the classification accuracy of the traditional paradigm; however the difference noted in certain subjects was minimal.

4.2 Experimental paradigm analysis

Three sets of experiments were conducted:

- a traditional paradigm as per the ERP testing technique discussed in Luck (2005) which includes a button push;
- the multi-class paradigm utilising the button pushing technique; and,
- the proposed multi-class paradigm using silent counting of the targets (the count was verified post each experiment – see Appendix K).

Note: the multi-class paradigms still utilised most of the rules and strategies documented by Luck (2005) with regards to ERP testing techniques. The tests revealed the accuracies in Table 4.1 to Table 4.4.

Table 4.1 Classification accuracies of the experimental paradigms using no signal processing. Accuracies are in percentages. * = with button pushing, ** = with silent counting.

Subject	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
1		65.7	63.0	80.0	62.0	63.0
2	70.0	63.0	61.0		65.3	74.7
3		65.3	63.3	76.7	80.7	75.0
4	69.2	63.3	67.3		62.3	68.0
5		60.0	61.7	73.3	62.0	64.7
6	74.2	61.0	68.3		72.0	68.7
7		58.7	57.3	74.2	61.7	63.0
8	67.5	62.0	63.3		58.7	64.3
9		64.7	62.0	85.0	64.3	69.7
10	80.0	63.7	71.0		68.7	74.7
11		60.3	67.0	83.3	76.3	66.0
12	62.5	62.3	57.3		62.7	65.3
13		58.7	67.3	70.8	71.0	66.0
14	69.2	60.3	58.7		63.3	64.7
15		62.0	61.0	71.7	64.3	68.0
Average	**70.4**	**62.1**	**63.3**	**76.9**	**66.4**	**67.7**

Table 4.2 Classification accuracies of the experimental paradigms using PCA signal processing. Accuracies are in percentages. * = with button pushing, ** = with silent counting.

Subject	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
1		96.0	93.7	98.3	99.7	99.7
2	97.5	94.7	98.3		99.7	100.0
3		97.7	98.7	100.0	99.7	99.7
4	96.7	90.3	96.0		97.3	98.7
5		91.7	93.7	97.5	100.0	98.7
6	95.8	98.7	97.3		98.3	99.3
7		92.3	87.3	94.2	97.3	98.7
8	95.8	96.3	96.7		97.7	99.7
9		98.7	97.3	100.0	99.7	100.0
10	100.0	97.3	96.7		99.3	98.0
11		97.0	98.7	99.2	99.3	99.3
12	95.8	96.3	95.0		95.0	95.3
13		95.3	95.7	93.3	99.0	99.3
14	97.5	96.7	93.0		95.3	95.3
15		96.3	96.7	97.5	96.3	98.0
Average	**97.0**	**95.7**	**95.6**	**97.5**	**98.2**	**98.6**

Table 4.3 Classification accuracies of the experimental paradigms using a combination of PCA and ICA signal processing. Accuracies are in percentages. * = with button pushing, ** = with silent counting.

Subject	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
1		67.0	66.3	75.0	60.7	64.3
2	71.7	60.7	58.0		65.0	77.0
3		67.0	64.7	75.0	79.0	75.0
4	66.7	66.7	64.7		59.3	66.3
5		66.3	61.7	70.0	65.3	61.7
6	75.8	60.7	66.3		72.3	70.0
7		61.0	56.7	69.2	62.0	60.3
8	65.8	60.3	61.0		60.7	65.7
9		65.7	61.0	87.5	63.7	75.7
10	82.5	67.0	72.0		72.3	72.7
11		65.3	69.0	87.5	76.0	65.7
12	70.8	66.3	57.0		57.3	63.3
13		63.7	62.3	74.2	70.7	66.3
14	70.8	61.3	57.0		59.3	67.3
15		65.7	62.3	75.0	68.7	68.0
Average	**72.0**	**64.3**	**62.7**	**76.7**	**66.2**	**68.0**

Table 4.4 Classification accuracies of the experimental paradigm using a combination of PCA and ICA signal processing with temporal and spatial manipulation. Accuracies are in percentages. * = with button pushing, ** = with silent counting.

Subject	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
1		66.3	61.0	80.8	58.7	59.7
2	75.8	58.0	59.3		66.3	66.7
3		63.7	64.0	77.5	76.3	68.7
4	66.7	63.7	59.3		60.7	59.3
5		62.0	59.7	70.0	62.0	70.3
6	76.7	61.7	68.0		68.0	67.3
7		61.7	61.0	65.0	65.3	63.0
8	65.8	59.3	63.0		61.7	61.3
9		58.7	63.7	80.0	61.0	68.0
10	69.2	61.0	66.7		64.7	67.7
11		61.0	65.7	74.2	75.7	59.0
12	62.5	64.0	54.7		63.3	64.3
13		59.3	58.0	74.2	70.3	64.0
14	74.2	58.3	61.7		57.7	61.3
15		66.3	68.0	77.5	71.0	70.3
Average	**70.1**	**61.7**	**62.2**	**74.9**	**65.5**	**64.7**

4.2.1 Analysis of Results

The results revealed that the traditional paradigm proves, on average, more accurate across the stimulus modalities and signal processing techniques than the multi-class paradigms. The multi-class paradigm with button pushing did not prove superior in performance to the paradigm with silent counting. A study conducted by Salisbury et al. (2001) concluded that button pushing affected P300 amplitude and scalp topography. The average sensitivity, specificity, PPV and NPV values for each paradigm are shown from Table 4.5 to Table 4.8.

Table 4.5 Sensitivity, specificity, PPV, and NPV average percentages for the experimental paradigms after no signal processing. * = with button pushing, ** = with silent counting.

	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
Specificity	70.0	63.0	64.7	78.6	65.3	68.4
Sensitivity	72.9	60.2	65.0	76.7	68.9	66.2
PPV	70.9	44.9	50.2	78.2	50.1	51.3
NPV	72.1	76.1	77.2	77.2	80.8	80.2

Table 4.6 Sensitivity, specificity, PPV, and NPV average percentages for the experimental paradigms after PCA signal processing. * = with button pushing, ** = with silent counting.

	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
Specificity	100.0	100.0	100.0	100.0	100.0	100.0
Sensitivity	95.2	86.9	87.2	95.0	95.1	95.4
PPV	100.0	100.0	100.0	100.0	100.0	100.0
NPV	95.5	94.0	94.0	95.5	97.7	97.8

Table 4.7 Sensitivity, specificity, PPV, and NPV average percentages for the experimental paradigms after PCA and ICA signal processing (without manipulation). * = with button pushing, ** = with silent counting.

	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
Specificity	73.8	65.5	63.0	76.9	65.5	63.0
Sensitivity	72.6	61.6	66.3	76.9	61.6	66.3
PPV	73.6	47.3	49.8	77.3	47.3	49.8
NPV	73.0	77.4	77.4	76.8	77.4	77.4

Table 4.8 Sensitivity, specificity, PPV, and NPV average percentages for the experimental paradigms after PCA and ICA signal processing (with manipulation). * = with button pushing, ** = with silent counting.

	Auditory			Visual		
	Traditional*	**Multi-class***	**Multi-class****	**Traditional***	**Multi-class***	**Multi-class****
Specificity	72.1	63.1	64.0	73.3	65.8	65.8
Sensitivity	69.8	57.9	61.4	75.7	63.9	61.4
PPV	71.3	44.0	48.4	74.1	48.5	47.4
NPV	70.8	75.0	75.4	75.6	78.4	77.4

4.2.2 Sub conclusions

Although the traditional paradigm proved more accurate, the accuracies obtained using the multi-class paradigm and PCA indicated that there is potential for FES application. Lower accuracies for multi-class paradigms can be attributed to increased task difficulty compared to the traditional paradigm (Kok 2001). By manipulating the multi-class paradigm to lower the task difficulty (e.g. via stimulus presentation methods) the classification accuracies of the P300 could possibly be improved.

4.3 Stimulus modality analysis

The two external stimulus modalities used in the paradigms were:

- auditory (presented using the earphones discussed in section 3.1.1); and,
- visual (presented using a CRT monitor).

The results revealed the accuracies in Table 4.9 to Table 4.11.

Table 4.9 Classification accuracies of auditory and visual stimuli for the traditional paradigm. Accuracies are in percentages. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

Subject	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**
1		80.0		98.3		75.0		80.8
2	70.0		97.5		71.7		75.8	
3		76.7		100.0		75.0		77.5
4	69.2		96.7		66.7		66.7	
5		73.3		97.5		70.0		70.0
6	74.2		95.8		75.8		76.7	
7		74.2		94.2		69.2		65.0
8	67.5		95.8		65.8		65.8	
9		85.0		100.0		87.5		80.0
10	80.0		100.0		82.5		69.2	
11		83.3		99.2		87.5		74.2
12	62.5		95.8		70.8		62.5	
13		70.8		93.3		74.2		74.2
14	69.2		97.5		70.8		74.2	
15		71.7		97.5		75.0		77.5
Average	**70.4**	**76.9**	**97.0**	**97.5**	**72.0**	**76.7**	**70.1**	**74.9**
Difference	**6.5**		**0.5**		**4.7**		**4.8**	

Table 4.10 Classification accuracies of auditory and visual stimuli for the multi-class paradigm (using button pushing). Accuracies are in percentages. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

Subject	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	Visual	Auditory	Visual	Auditory	Visual	Auditory	Visual
1	65.7	62.0	96.0	99.7	67.0	60.7	66.3	58.7
2	63.0	65.3	94.7	99.7	60.7	65.0	58.0	66.3
3	65.3	80.7	97.7	99.7	67.0	79.0	63.7	76.3
4	63.3	62.3	90.3	97.3	66.7	59.3	63.7	60.7
5	60.0	62.0	91.7	100.0	66.3	65.3	62.0	62.0
6	61.0	72.0	98.7	98.3	60.7	72.3	61.7	68.0
7	58.7	61.7	92.3	97.3	61.0	62.0	61.7	65.3
8	62.0	58.7	96.3	97.7	60.3	60.7	59.3	61.7
9	64.7	64.3	98.7	99.7	65.7	63.7	58.7	61.0
10	63.7	68.7	97.3	99.3	67.0	72.3	61.0	64.7
11	60.3	76.3	97.0	99.3	65.3	76.0	61.0	75.7
12	62.3	62.7	96.3	95.0	66.3	57.3	64.0	63.3
13	58.7	71.0	95.3	99.0	63.7	70.7	59.3	70.3
14	60.3	63.3	96.7	95.3	61.3	59.3	58.3	57.7
15	62.0	64.3	96.3	96.3	65.7	68.7	66.3	71.0
Average	**62.1**	**66.4**	**95.7**	**98.2**	**64.3**	**66.2**	**61.7**	**65.5**
Difference	**4.3**		**2.5**		**1.9**		**3.8**	

Table 4.11 Classification accuracies of auditory and visual stimuli for the multi-class paradigm (using silent counting). Accuracies are in percentages. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

Subject	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	Visual	Auditory	Visual	Auditory	Visual	Auditory	Visual
1	63.0	63.0	93.7	99.7	66.3	64.3	61.0	59.7
2	61.0	74.7	98.3	100.0	58.0	77.0	59.3	66.7
3	63.3	75.0	98.7	99.7	64.7	75.0	64.0	68.7
4	67.3	68.0	96.0	98.7	64.7	66.3	59.3	59.3
5	61.7	64.7	93.7	98.7	61.7	61.7	59.7	70.3
6	68.3	68.7	97.3	99.3	66.3	70.0	68.0	67.3
7	57.3	63.0	87.3	98.7	56.7	60.3	61.0	63.0
8	63.3	64.3	96.7	99.7	61.0	65.7	63.0	61.3
9	62.0	69.7	97.3	100.0	61.0	75.7	63.7	68.0
10	71.0	74.7	96.7	98.0	72.0	72.7	66.7	67.7
11	67.0	66.0	98.7	99.3	69.0	65.7	65.7	59.0
12	57.3	65.3	95.0	95.3	57.0	63.3	54.7	64.3
13	67.3	66.0	95.7	99.3	62.3	66.3	58.0	64.0
14	58.7	64.7	93.0	95.3	57.0	67.3	61.7	61.3
15	61.0	68.0	96.7	98.0	62.3	68.0	68.0	70.3
Average	**63.3**	**67.7**	**95.6**	**98.6**	**62.7**	**68.0**	**62.2**	**64.7**
Difference	**4.4**		**3.0**		**5.3**		**2.5**	

4.3.1 Analysis of Results

The visual paradigms proved slightly superior in performance to the auditory classification paradigms. This difference in accuracy diminished across the signal processing techniques for the traditional paradigm and indicates that by utilisation of signal processing the auditory P300 can more comparably be identified by the classifier (i.e. the difference in S/N ratio between visual and auditory P300s contributing to classification differences, is reduced). The average sensitivity, specificity, PPV and NPV values for each paradigm are shown from Table 4.12 to Table 4.14.

Table 4.12 Sensitivity, specificity, PPV, and NPV average percentages for the stimulus modalities using the traditional paradigm. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**
Specificity	70.0	78.6	100.0	100.0	73.8	76.9	72.1	73.3
Sensitivity	72.9	76.7	95.2	95.0	72.6	76.9	69.8	75.7
PPV	70.9	78.2	100.0	100.0	73.6	77.3	71.3	74.1
NPV	72.1	77.2	95.5	95.5	73.0	76.8	70.8	75.6

Table 4.13 Sensitivity, specificity, PPV, and NPV average percentages for the stimulus modalities using the multi-class paradigm (with button pushing). * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**
Specificity	63.0	65.3	100.0	100.0	65.5	65.5	63.1	65.8
Sensitivity	60.2	68.9	86.9	95.1	61.6	61.6	57.9	63.9
PPV	44.9	50.1	100.0	100.0	47.3	47.3	44.0	48.5
NPV	76.1	80.8	94.0	97.7	77.4	77.4	75.0	78.4

Table 4.14 Sensitivity, specificity, PPV, and NPV average percentages for the stimulus modalities using the multi-class paradigm (with silent counting). * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation.

	None		PCA		PCA and ICA*		PCA and ICA**	
	Auditory	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**	**Auditory**	**Visual**
Specificity	64.7	68.4	100.0	100.0	63.0	63.0	64.0	65.8
Sensitivity	65.0	66.2	87.2	95.4	66.3	66.3	61.4	61.4
PPV	50.2	51.3	100.0	100.0	49.8	49.8	48.4	47.4
NPV	77.2	80.2	94.0	97.8	77.4	77.4	75.4	77.4

4.3.2 Sub conclusions

Accuracies obtained from some auditory experiments support further investigation into potential online FES application. However this predominantly applies to the utilisation of PCA as a signal processing technique. Certain subjects (1, 4, 12 and 14) in Table 4.10 showed accuracies higher in auditory paradigms versus visual stimulus paradigms, which indicate that performance can be subject-specific and tailoring the paradigm to match the subject's best possible probability of correctly identifying target and non-target information is crucial.

4.4 Signal processing analysis

The signal processing techniques used for single-trial P300 classification included:

- no signal processing (the classifier was trained on the signal processed extracted epochs);
- PCA;
- PCA and ICA (without manipulation); and,
- PCA and ICA with temporal and spatial manipulation.

The accuracies are shown in Table 4.15 and Table 4.16.

Table 4.15 Classification accuracies of the signal processing techniques for auditory stimuli. Accuracies are in percentages. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation, *** = with button pushing, **** = with silent counting.

Subject	Traditional***				Multi-class***				Multi-class****			
	None	PCA	PCA & ICA*	PCA & ICA**	None	PCA	PCA & ICA*	PCA & ICA**	None	PCA	PCA & ICA*	PCA & ICA**
1					65.7	96.0	67.0	66.3	63.0	93.7	66.3	61.0
2	70.0	97.5	71.7	75.8	63.0	94.7	60.7	58.0	61.0	98.3	58.0	59.3
3					65.3	97.7	67.0	63.7	63.3	98.7	64.7	64.0
4	69.2	96.7	66.7	66.7	63.3	90.3	66.7	63.7	67.3	96.0	64.7	59.3
5					60.0	91.7	66.3	62.0	61.7	93.7	61.7	59.7
6	74.2	95.8	75.8	76.7	61.0	98.7	60.7	61.7	68.3	97.3	66.3	68.0
7					58.7	92.3	61.0	61.7	57.3	87.3	56.7	61.0
8	67.5	95.8	65.8	65.8	62.0	96.3	60.3	59.3	63.3	96.7	61.0	63.0
9					64.7	98.7	65.7	58.7	62.0	97.3	61.0	63.7
10	80.0	100.0	82.5	69.2	63.7	97.3	67.0	61.0	71.0	96.7	72.0	66.7
11					60.3	97.0	65.3	61.0	67.0	98.7	69.0	65.7
12	62.5	95.8	70.8	62.5	62.3	96.3	66.3	64.0	57.3	95.0	57.0	54.7
13					58.7	95.3	63.7	59.3	67.3	95.7	62.3	58.0
14	69.2	97.5	70.8	74.2	60.3	96.7	61.3	58.3	58.7	93.0	57.0	61.7
15					62.0	96.3	65.7	66.3	61.0	96.7	62.3	68.0
Average	**70.4**	**97.0**	**72.0**	**70.1**	**62.1**	**95.7**	**64.3**	**61.7**	**63.3**	**95.6**	**62.7**	**62.2**

Table 4.16 Classification accuracies of the signal processing techniques for visual stimuli. Accuracies are in percentages. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation, *** = with button pushing, **** = with silent counting.

Subject	Traditional***				Multi-class***				Multi-class****			
	None	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****
1	80.0	98.3	75.0	80.8	62.0	99.7	60.7	58.7	63.0	99.7	64.3	59.7
2					65.3	99.7	65.0	66.3	74.7	100.0	77.0	66.7
3	76.7	100.0	75.0	77.5	80.7	99.7	79.0	76.3	75.0	99.7	75.0	68.7
4					62.3	97.3	59.3	60.7	68.0	98.7	66.3	59.3
5	73.3	97.5	70.0	70.0	62.0	100.0	65.3	62.0	64.7	98.7	61.7	70.3
6					72.0	98.3	72.3	68.0	68.7	99.3	70.0	67.3
7	74.2	94.2	69.2	65.0	61.7	97.3	62.0	65.3	63.0	98.7	60.3	63.0
8					58.7	97.7	60.7	61.7	64.3	99.7	65.7	61.3
9	85.0	100.0	87.5	80.0	64.3	99.7	63.7	61.0	69.7	100.0	75.7	68.0
10					68.7	99.3	72.3	64.7	74.7	98.0	72.7	67.7
11	83.3	99.2	87.5	74.2	76.3	99.3	76.0	75.7	66.0	99.3	65.7	59.0
12					62.7	95.0	57.3	63.3	65.3	95.3	63.3	64.3
13	70.8	93.3	74.2	74.2	71.0	99.0	70.7	70.3	66.0	99.3	66.3	64.0
14					63.3	95.3	59.3	57.7	64.7	95.3	67.3	61.3
15	71.7	97.5	75.0	77.5	64.3	96.3	68.7	71.0	68.0	98.0	68.0	70.3
Average	**76.9**	**97.5**	**76.7**	**74.9**	**66.4**	**98.2**	**66.2**	**65.5**	**67.7**	**98.6**	**68.0**	**64.7**

4.4.1 Analysis of Results

By using a combination of PCA and ICA the classification accuracy did not vastly improve compared with epochs which have not undergone any signal processing. In some instances the accuracy worsened. This can additionally be seen in the specificity and sensitivity scores. By temporally and spatially manipulating data the accuracy also did not improve. The conventional PCA methodology proved the superior choice of signal processing with vastly improved accuracy scores. These results were further enhanced by the average sensitivity, specificity, PPV and NPV values for each paradigm shown in Table 4.17 and Table 4.18. A few subjects scored 100% classification accuracies in certain experimental paradigms.

Table 4.17 Sensitivity, specificity, PPV, and NPV average percentages for the different signal processing techniques using auditory stimuli. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation, *** = with button pushing, **** = with silent counting.

	Traditional***				Multi-class***				Multi-class****			
	None	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****
Sensitivity	70.0	100.0	73.8	72.1	63.0	100.0	65.5	63.1	64.7	100.0	63.0	64.0
Specificity	72.9	95.2	72.6	69.8	60.2	86.9	61.6	57.9	65.0	87.2	66.3	61.4
PPV	70.9	100.0	73.6	71.3	44.9	100.0	47.3	44.0	50.2	100.0	49.8	48.4
NPV	72.1	95.5	73.0	70.8	76.1	94.0	77.4	75.0	77.2	94.0	77.4	75.4

Table 4.18 Sensitivity, specificity, PPV, and NPV average percentages for the different signal processing techniques using visual stimuli. * = without temporal and spatial manipulation, ** = with temporal and spatial manipulation, *** = with button pushing, **** = with silent counting.

	Traditional***				Multi-class***				Multi-class****			
	None	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****	**None**	**PCA**	**PCA & ICA***	**PCA & ICA****
Sensitivity	78.6	100.0	76.9	73.3	65.3	100.0	65.5	65.8	68.4	100.0	63.0	65.8
Specificity	76.7	95.0	76.9	75.7	68.9	95.1	61.6	63.9	66.2	95.4	66.3	61.4
PPV	78.2	100.0	77.3	74.1	50.1	100.0	47.3	48.5	51.3	100.0	49.8	47.4
NPV	77.2	95.5	76.8	75.6	80.8	97.7	77.4	78.4	80.2	97.8	77.4	77.4

4.4.2 Sub conclusions

Detecting single-trial P300s using a combination of PCA and ICA does not provide sufficient scope for future FES control systems when utilising the chosen paradigms. However, by solely utilising PCA, accuracies of between 95% and 100% were obtained and provide a definite platform for investigation into online FES integration. The method of spatio-temporally enhancing or manipulating the P300 characteristics indicates that it does not provide for improved classification results for this set of experiments.

4.5 Group Statistics

Statistical analysis using Analysis of Variance (ANOVA) allows testing of the existence of a statistically significant difference amongst several groups of data. The test uses variances to determine whether the means of the data are equal or not. The three assumptions to be fulfilled include:

- each population from which a sample is taken is assumed to be normal;
- each sample is randomly selected and independent; and,
- the populations are assumed to have equal standard deviations (or variances).

4.5.1 Analysis of the stimulus techniques

The group statistical comparison between auditory and visual stimuli was made by choosing:

- the multi-class (silent counting) algorithm – in line with the objectives towards future research into potential hands-free FES-BCI integration; and,
- the PCA signal processing technique – as determined through the sensitivity, specificity, PPV, and NPV statistical results achieved in the section 4.4.1 as providing the best signal processing technique for classification accuracy.

The single factor (or one-way) ANOVA table of results across the 15 subjects can be seen in Table 4.19.

Table 4.19 Single factor ANOVA results for auditory and visual comparative variance. SS = sum of squares; df = degrees of freedom; MS = mean squares (SS/df); F = F statistic; and p = p-value for F.

Source	SS	df	MS	F	p
Stimulus Types	67.47	1	67.47	12.61	0.0014
Errors (or Residuals)	149.864	28	5.3523		
Total	217.334	29			

The very small *p*-value indicates that differences between auditory and visual mean results are significant (indicating the null hypothesis is false). The post hoc test reveals the 'box plot' graph in Figure 4.1 which indicates the overall improved accuracy if using a visual stimulus and also indicating that there is a difference between the two.

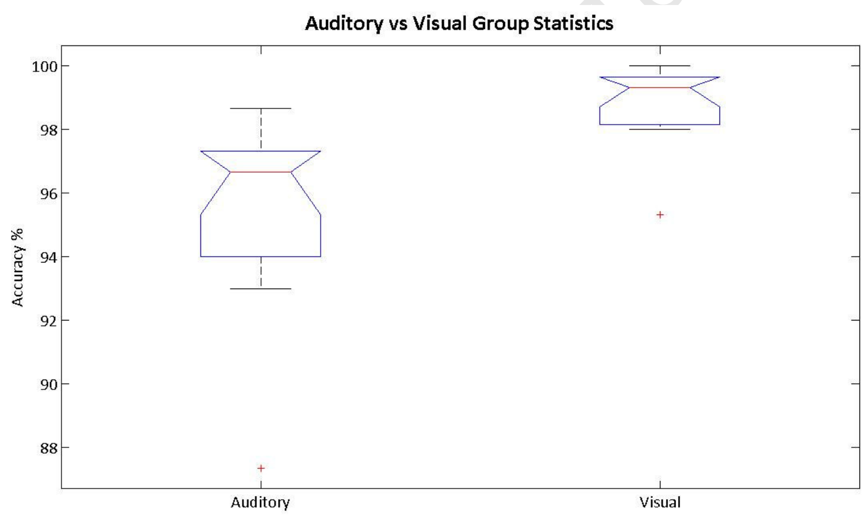

Figure 4.1 Boxplot of auditory and visual comparative variance.

This result agrees with the literature discussed in section 2.5.1.2 that overall a visual stimulus should provide more accurate results. Additionally, since the visual stimulus paradigms succeeded the auditory stimulus paradigms across the subject group in terms of task order, the visual stimulus results may have been more accurate if the effects of fatigue and habituation are taken into account but the comparative outcome of visual performing better than auditory would remain.

4.5.2 Analysis of experimental paradigms

The factors used in the statistical approach for comparing the traditional and multi-class paradigms (with button pushing since the traditional paradigm was conducted with button pushing) were as follows:

- the auditory stimulus – in line with the investigation of an auditory BCI system; and,
- the PCA signal processing technique - as determined through the sensitivity, specificity, PPV, and NPV statistical results achieved in the section 4.4.1 as providing the best signal processing technique for classification accuracy.

The table of results from the single factor ANOVA can be seen in Table 4.20.

Table 4.20 Single factor ANOVA results for traditional and multi-class comparative variance. SS = sum of squares; df = degrees of freedom; MS = mean squares (SS/df); F = F statistic; and p = p-value for F.

Source	SS	df	MS	F	p
Experimental Paradigms	8.496	1	8.49567	1.71	0.206
Errors (or Residuals)	99.434	20	4.97169		
Total	107.929	21			

The *p*-value of 0.206 would statistically not reject the null hypothesis, indicating little difference between the traditional and multi-class means across the subjects, however the literature (see section 2) and for most results obtained in the statistics covered by sensitivity and specificity indicate that the traditional paradigm would produce the best classification accuracies. The *p*-value also indicates the probability of this outcome under the null hypothesis is 0.206. The post hoc test, seen in Figure 4.2, confirms the small difference in mean values between traditional and multi-class experimental paradigms. However there is a slight overall improvement when using the traditional paradigm (corroborated by the literature). Additionally factors such as fatigue and habituation may have affected the traditional paradigm's accuracies due to the lack of counterbalancing the task order.

Thus it is difficult to make a conclusive comparative analysis between the experimental paradigms.

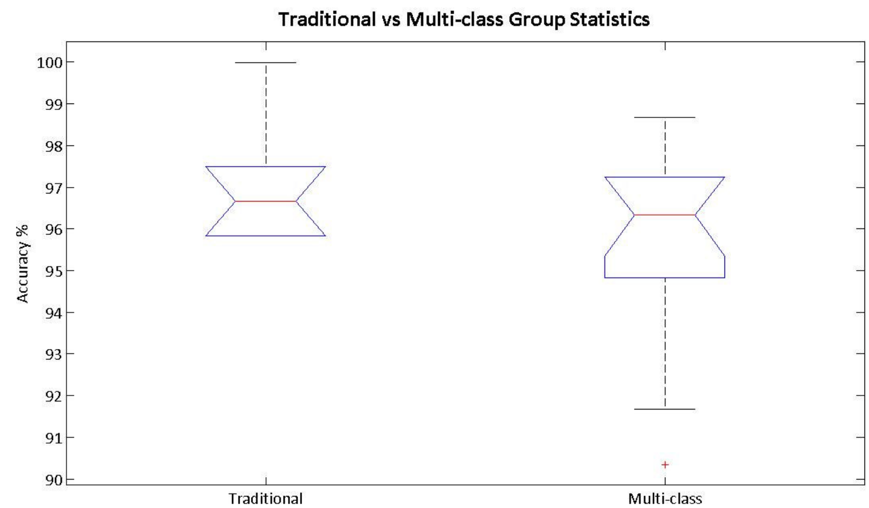

Figure 4.2 Boxplot of traditional and multi-class comparative variance.

Additionally the null hypothesis was accepted when comparing button pushing and silent counting. A *p*-value of 0.963 indicates that there is negligible difference between the two and/or there is not enough evidence to suggest a difference. Figure 4.3 also suggested very little difference between the two techniques. However due to the techniques not being counterbalanced (to cater for habituation and/or fatigue) a conclusive result can't be made due to the silent counting always preceding the button pushing technique. The effects of fatigue and habituation may have adversely affected the button pushing technique's results.

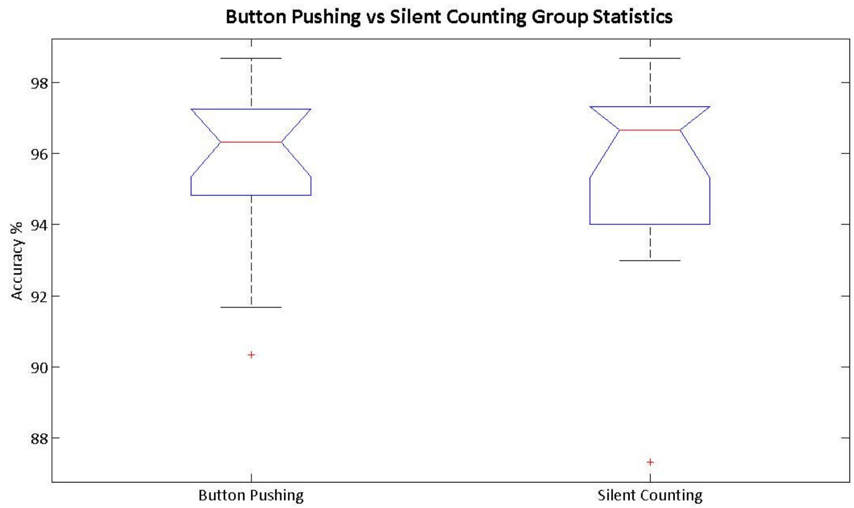

Figure 4.3 Boxplot of button pushing and silent counting comparative variance.

4.5.3 Analysis of signal processing techniques

In investigating the ANOVA and post hoc tests for the different signal processing techniques, the auditory multi-class (silent counting) algorithm was adopted in line with the objectives of the thesis. This ideally would help to highlight the best signal processing technique for the proposed paradigm and also give an indication of the variance across the group for the various techniques.

Table 4.21 Single factor ANOVA results for comparison of signal processing variance. SS = sum of squares; df = degrees of freedom; MS = mean squares (SS/df); F = F statistic; and p = p-value for F.

Source	SS	df	MS	F	p
Signal Processing Techniques	12189.4	3	4063.12	266.5	0
Errors (or Residuals)	853.8	56	15.25		
Total	13043.1	59			

A *p*-value of 0 indicates complete rejection of the null hypothesis (i.e. that there is no significant difference between the techniques). The probability that the signal processing techniques for this paradigm would be different is 100%. The sensitivity and specificity scores in section 4.4.1 additionally indicate the superior performance of PCA over the other signal processing techniques. This is corroborated via the post hoc test seen in Figure 4.4, which evidently suggests PCA as the best signal processing technique across the subjects.

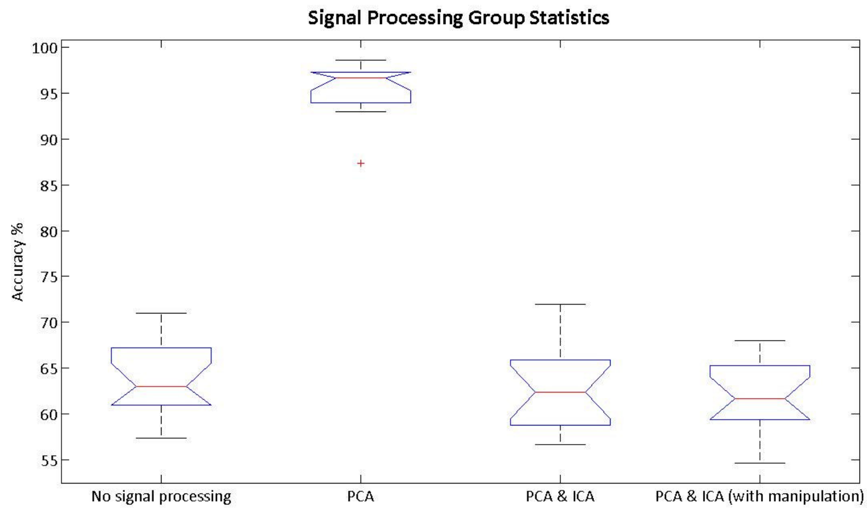

Figure 4.4 Boxplot of signal processing comparative variance.

Additionally counterbalancing (i.e. to mitigate the effects of habituation and/or fatigue across the subject group statistics) would not affect the comparison of the signal processing techniques due to the analysis being within a task dataset rather than across datasets i.e. the signal processing comparison only applies to the auditory multi-class (silent counting) experimental paradigm.

4.5.4 Multi-way Statistical Analysis

Table 4.22 Comparative table of the means, Standard Error of the Mean (SEM), and the relative 95% Confidence Intervals. * = with spatio-temporal manipulation.

Stimulus Type	Experimental Paradigm	Signal Processing Technique	Mean	SEM	95% Confidence Interval	
					Lower	Upper
Auditory	Traditional	None	70.37	2.07	65.30	75.44
		PCA	97.01	0.58	95.61	98.42
		PCA & ICA	72.01	2.15	66.75	77.28
		PCA & ICA*	70.13	2.08	65.04	75.21
	Multi-class (with button pushing)	None	62.07	0.58	60.83	63.31
		PCA	95.69	0.64	94.31	97.06
		PCA & ICA	64.31	0.70	62.81	65.81
		PCA & ICA*	61.67	0.70	60.17	63.16
	Multi-class (with silent counting)	None	63.30	1.06	61.02	65.58
		PCA	95.65	0.75	94.04	97.27
		PCA & ICA	62.67	1.18	60.15	65.19
		PCA & ICA*	62.25	0.99	60.13	64.38
Visual	Traditional	None	76.88	1.89	72.40	81.35
		PCA	97.50	0.89	95.39	99.61
		PCA & ICA	76.68	2.50	70.77	82.58
		PCA & ICA*	74.90	1.88	70.46	79.34
	Multi-class (with button pushing)	None	66.35	1.59	62.94	69.76
		PCA	98.24	0.43	97.31	99.17
		PCA & ICA	66.15	1.72	62.46	69.84
		PCA & ICA*	65.51	1.49	62.33	68.70
	Multi-class (with silent counting)	None	67.72	1.07	65.42	70.02
		PCA	98.65	0.39	97.82	99.48
		PCA & ICA	67.95	1.32	65.12	70.79
		PCA & ICA*	64.73	1.03	62.52	66.94

As can be seen in Table 4.22, within each of the six experimental paradigms there is a complete overlap of the confidence intervals for three out of the four signal processing techniques i.e. none of these outcomes is significantly different from the other. Only PCA stands out and there is no overlap between the confidence intervals for *this* treatment and for any of the other three. That being the case it is safe to conclude that the PCA signal processing technique provides a significantly better result at the 0.05 level of probability.

When comparing auditory and visual what we see is that, whereas the means are higher for the visual PCA results, there is again a lot of overlap of the confidence intervals – indicating that the auditory outcomes may not be significantly worse than the visual. However counterbalancing the tasks would have categorically enabled this conclusion to be reached.

After conducting a three factor (three-way) ANOVA, the null hypothesis that all four signal processing techniques will produce the same results is rejected (see Table 4.23).

Table 4.23 Three factor (multi-way) ANOVA of classification accuracies. SS = sum of squares; df = degrees of freedom; MS = mean squares (SS/df); F = F statistics; and p = p-value for F statistics.

Source	SS	df	MS	F	p
Stimulus Types	1046	1	1046.5	51.33	6.35E-12
Experimental Paradigms	2205	2	1102.5	54.08	2.20E-16
Signal Processing Techniques	53210	3	17736.8	869.96	2.20E-16
Errors (or Residuals)	5974	293	20.4		
Total	62435	299			

However, when PCA is removed from the analysis (as in Table 4.24), we see that the *p*-value is > 0.05 so at a 5% level of significance the null hypothesis that the methods are the same is not rejected. This indicates the superior processing benefit that PCA provides the classification accuracy.

Table 4.24 Three factor (multi-way) ANOVA of classification accuracies. * = signal processing techniques excluding PCA. SS = sum of squares; df = degrees of freedom; MS = mean squares (SS/df); F = F statistics; and p = p-value for F statistics.

Source	SS	df	MS	F	p
Stimulus Types	995.4	1	995.38	44.74	1.85E-10
Experimental Paradigms	2906.5	2	1453.26	65.32	2.20E-16
Signal Processing Techniques*	123.8	2	61.91	2.78	0.06407
Errors	4872.4	219	22.25		
Total	8898.1	224			

4.6 Summary of results

The main findings are summarised below. Some relevant implications of these findings will be discussed in the next chapter.

1. classification of visual stimulus paradigms overall produced more accurate results;

2. however, certain subjects revealed superior classification accuracies for auditory paradigms;

3. PCA proved to be the signal processing technique that provided the best classification platform for the LSVM;

4. a combination of PCA and ICA did not improve classification accuracies for these paradigms; and,

5. additionally, temporal and spatial manipulation of the waveforms did not provide enhanced classification results.

Two other notable observations include:

1. the traditional paradigm proved slightly superior in performance to the multi-class paradigms; and,

2. the button pushing technique did not improve classification accuracies, however.

These observations, however, can't be decisively made due to a lack of counterbalancing across the tasks confounding the results.

A discussion of these results can be found in Chapter 5.

5 Discussion

This chapter documents the more detailed discussion on the results found for the experimental paradigms, the external stimulus modalities, and the various signal processing techniques.

5.1 Testing setup

Many subjects reported that they started feeling tired towards the end of the experiments (thus the compromise on the number of trials versus the need for preferably more ERPs for analysis was maximised). This fatigue and corresponding lack of attention is evident in subjects 2, 4, 7 and 5, where there is a difference in the verified count and the actual count (refer to Appendix K). Additionally high impedance measures (negatively impacting the recording) were found on certain subjects due to the subjects' scalp conditions or the application of KCL. For example, the visual multi-class paradigm for subject 14 required as many as 30 bad channels to be manually removed from the recording (refer to Appendix K).

Certain subjects also complained about the ergonomic setup of the experiment. This contributed to factors such as abnormal breathing, shaking, and muscle stiffness. Also most subjects reported that classifying the auditory stimuli was more difficult than the visual stimuli and that button pushing was easier than silent counting. Some subjects found it difficult to focus on the background (i.e. the cross-hair) which caused excessive blinking or blurring of vision.

Lastly four subjects reported that they lost concentration and their thoughts wondered. This sometimes resulted in them occasionally referring back to the previous experiment's target.

5.2 Performance of the experimental paradigms

Classification accuracies for the traditional paradigms were lower than expected using the combination of PCA and ICA and by temporally and spatially manipulating the data. Contributing factors included the probability of the target stimulus being 50% as opposed to other traditional paradigms where the target stimulus has an extremely low probability compared with non-target (or standard) stimuli. The literature reveals that with decreased probability, increased P300 amplitude is experienced (see Appendix D). However due to an aim of this thesis being to create a paradigm for 'real' environment applicability, the probability of all potential targets was chosen to be the same.

The average percentage of correct classifications (PPV) for the traditional paradigms was above 70% for all signal processing techniques and stimulus types (i.e. auditory or visual). Subject 1, 9 and 10 obtained a classification accuracy of 100% for the auditory (subject 1) and visual (subject 9 and 10) traditional paradigms using the PCA signal processing technique.

In general, the multi-class paradigms proved less accurate than the traditional paradigm (this could be attributed to increased task difficulty); however for certain subjects this wasn't the case. Additionally the possible negative effects that habituation and/or fatigue may have had on the traditional paradigm make it difficult to find a conclusive result (this is due to a lack of counterbalancing the tasks). A possibility (identified through the literature), as to why certain subjects performed better for the multi-class paradigm, could be due to the fact that there is a decreased probability of the target stimulus (33.3%) versus the non-target stimuli (66.7%), compared with the traditional paradigm adopted (i.e. 50% versus 50%). Although the traditional paradigm proved to produce superior classification accuracies, Table 5.1 shows which subjects achieved higher accuracy results for multi-class paradigms over the traditional paradigms.

Table 5.1 An indication of which subjects scored higher classification accuracies for the multi-class paradigms over the traditional paradigms for each of the signal processing and stimulus techniques. ✓ = multi-class proved superior.

	No signal processing		PCA		PCA & ICA		PCA & ICA with manipulation	
Subject	Auditory	Visual	Auditory	Visual	Auditory	Visual	Auditory	Visual
1				✓				
2			✓					
3		✓				✓		
4								✓
5				✓				
6			✓					
7				✓				✓
8			✓					
9								
10								
11				✓				✓
12			✓				✓	
13				✓				
14								
15				✓				

Two major disadvantages of P300 BCIs are:

- the effect of habituation causing a reduction in P300 amplitude (thus over the experimental paradigm the generation of the P300 may be diminished resulting in decreased classification accuracies (Romero, Polich 1996) e.g. a subject may have been given the same target for successive visual or auditory paradigms because they are randomly chosen); and,

- the reduction in amplitude of multi-class (or multi-choice) generated P300s not only due to task difficulty but also due to lower discriminality between external stimuli (Kok 2001).

For all signal processing techniques apart from PCA, the traditional paradigms scored (on average) between 70% and 77%. The multi-class paradigms scored (on average) between 61% and 67% for paradigms which included the button pushing, and (on average) between 62% and 68% for paradigms which included silent counting. Although the ERP testing technique discussed by Luck (2005) recommends button pushing to identify target ERPs, the investigation conducted by Salisbury et al. (2001) indicated that button pushing can attenuate the P300 amplitude and distort scalp topography. It should also be noted that in instances where the button push for target and non-target stimuli didn't correlate with the direction of arrows being presented, subjects complained of increased task difficulty. This is supported by the incongruency effect which results in increased P300 latency beyond the theoretical 300 ms post the stimulus (Rothermund, Gast & Wentura 2011). This would result in an apparent shift in the temporal window of the P300 features and hence may possibly fall outside the feature space defined by the signal processing prior to classification, thereby affecting the classification results negatively. The traditional visual paradigm used up and down arrows and hence this was only experienced in the multi-class paradigms.

PCA boosted the classification accuracies to between 95% and 100% for the traditional paradigms, between 90% and 100% for button pushing multi-class paradigms, and between 87% and 100% for silent counting multi-class paradigms. The multi-class paradigms proved to have very low PPV scores compared with the sensitivity, specificity, and NPV percentages for all signal processing techniques except PCA, indicating that a higher percentage of false positives were classified compared with false negatives. This adversely affects the specificity of the classification. Scores of 100% for specificity and PPV were obtained across all experimental paradigms utilising PCA signal processing, indicating that zero stimuli were incorrectly identified as a target.

5.3 The auditory and visual stimulus comparison

Overall, visual paradigms proved superior in classification performance to auditory paradigms (as expected from the literature), however certain subjects revealed that for some paradigms, auditory classification proved a better means of classifying target and non-target stimuli (Table 5.2).

Table 5.2 An indication of which subjects scored higher classification accuracies for the paradigms employing auditory stimuli over the paradigms employing visual stimuli for each of the multi-class paradigms. Note that the traditional paradigm isn't included for comparison because subjects only completed either an auditory or visual stimulus traditional paradigm - not both. * = temporal and spatial manipulation, ✓ = subjects scored higher auditory classification accuracies than visual.

Subject	Multi-class (button pushing)				Multi-class (silent counting)			
	None	PCA	PCA & ICA	PCA & ICA*	None	PCA	PCA & ICA	PCA & ICA*
1	✓		✓	✓			✓	✓
2								
3								
4	✓		✓	✓				
5			✓					
6		✓						✓
7								
8	✓							✓
9	✓		✓					
10								
11					✓		✓	✓
12		✓	✓	✓				
13					✓			
14		✓	✓	✓				✓
15								

In fact, of all multi-class experimental paradigms, 21.67% of the subjects' classification results revealed that auditory stimuli produced more accurate results for identifying the targets and non-targets. This finding is corroborated for patients suffering from ALS in the study conducted by Sellers et al. (2006). The fact that some subjects found it harder to distinguish between auditory tones compared with distinguishing between visual arrows, indicates that by increasing the difference in target and non-target auditory stimuli (e.g. via pitch, length, volume, type, etc.) may result in improved classification accuracies. Schreuder et al (2009) varied tone length and obtained accuracies of over 90% for most conditions.

Accuracies (on average) of between 61% and 72% resulted from paradigms employing auditory stimuli and signal processing techniques other than PCA. Visual stimulus paradigms resulted in accuracies of between 64% and 77% for the same criteria. Low PPV versus NPV scores for the multi-class paradigms indicate a proportionately higher number of falsely identifying targets versus falsely identifying non-targets. Additionally, in corroboration, sensitivity and specificity scores are comparatively similar. Utilising the PCA signal processing methodology resulted in accuracies of between 87% and 100% for auditory paradigms and between 95% and 100% for visual paradigms. PCA also improved the sensitivity, specificity, PPV and NPV percentages. Scores of 100% for specificity and PPV were obtained across both stimulus modalities and high sensitivity and NPV scores indicate that very few stimuli were incorrectly identified as non-targets.

In the multi-class paradigms the marginal difference between visual and auditory classification accuracies diminished slightly from approximately 6% on average to 4% on average[30]. This provides positive evidence for further research into auditory multi-class systems together with the proportion of subjects that

[30] Auditory generated P300 waveforms have a lower S/N ratio and hence have proven more difficult to classify.

identified auditory stimuli more readily than visual stimuli. However further research should be conducted with regards to counterbalancing the order of auditory and visual tasks so as to mitigate the effects of fatigue and/or habituation which may have reduced the classification accuracy of the visual results and hence the marginal difference between the stimulus types.

5.4 Signal processing performance

The method of PCA for data reduction and ICA for source extraction does not prove to be a more effective means of processing the EEG data for classification based on the explored experimental paradigms. In some instances the accuracy diminished with the addition of PCA and ICA, and furthermore for temporal and spatial manipulation. Table 5.3 indicates which subjects saw an improvement with the addition of PCA and ICA.

Given that P300 is can be a relatively distributed process (as opposed to highly spatially localised) it is possible that ICA may have split the P300 into process sub components, hence complicating the classification process. In which case, fine tuning of the classifier or selection of another classifier, could potentially improve results.

Table 5.3 An indication of whether a combination of PCA and ICA improved classification over no signal processing. # = auditory and visual, * = with button push, ** = without button push, ✓ = a combination of PCA and ICA improved classification over no signal processing.

		Auditory		Visual	
Subject	Traditional#	Multi-class*	Multi-class**	Multi-class*	Multi-class**
1			✓		✓
2	✓				✓
3		✓	✓		
4		✓			
5		✓		✓	
6	✓			✓	✓
7		✓		✓	
8				✓	✓
9	✓	✓			✓
10	✓	✓	✓	✓	
11	✓	✓	✓		
12	✓	✓			
13	✓	✓			✓
14	✓	✓			✓
15	✓	✓	✓	✓	

Therefore, from Table 5.3, only 50.77% of the recorded EEG was classified more accurately due to the addition of a 'PCA in combination with ICA' signal processing technique. Additionally only 36% of recorded experiments saw an improvement in classification accuracy with the advent of PCA in combination with ICA followed by temporal and spatial manipulation. This method was reliant on *a priori* knowledge of the inherent traditional characteristics of the P300 and hence factors outside of these affecting the classification (negatively or positively) were diminished by the enhancement. Thus for those P300 factors different (e.g. introduced by the Stroop effect – see section 5.2) to the assumed spatial and temporal properties of the P300, the process of manipulation would have a negative impact on the SVM output, which is indicative of the results. For example, if the peak of the P300 fell outside the pre-defined window for the temporal manipulation it was not included in the manipulated or enhanced data and hence would decrease the effectiveness of classification[31].

Spatial distribution of the peak amplitude, due to subject-perceived task difficulty, can shift towards the frontal region (Fz) (Hagen et al. 2006). A study conducted by Hagen et al. (2006) concluded that increased perceptual discrimination difficulty between target and standard stimuli increases the P3a[32]. Hence by favouring parietal (Pz) spatial distribution of the P300 can result in decreased classification accuracies with increased task difficulty (as introduced by the multi-class paradigm).

PCA in combination with ICA (on average) improved the classification accuracy by 2%. In some instances, utilising PCA as the sole signal processing

[31] Kurtosis approach or peak identification could rather have been used in the methodology.
[32] See Appendix D for P3a theory.

technique improved classification accuracies by over 30%. Very low PPV scores for multi-class paradigms indicate the LSVM's inability to correctly identify targets when utilising PCA in combination with ICA and when performing temporal and spatial enhancement of the data. PCA allows for high sensitivity, specificity, PPV and NPV values, indicating the classifiers ability to correctly identify targets and non-targets. Indications are that with increased task difficulty and multi-class systems using PCA as a base for classification is a much more effective means of signal processing, however this theory was only applicable to the adopted experimental paradigm techniques.

PCA provides an accurate signal processing technique and appears to be sufficient for a real time auditory multi-class P300 BCI. Whilst the author's results also indicate PCA out-performed the PCA and ICA combination, it can't be conclusively stated that ICA alone would not be equivalent to PCA alone unless, as recommended for further research, the ICA options are examined in greater detail.

Further work needs to be conducted beyond an offline single-trial classification to determine the processing efficiency in an online state. These are steps that need to be followed towards 'real' environment applicability as an asynchronous FES BCI.

With regards to the statistical measures of the auditory multi-class P300 paradigm with silent counting (as per the objectives of the investigation into potential further research), the results indicate a positive trend towards PCA as a signal processing tool; however more work should be conducted on researching other ICA techniques before an affirmative conclusion on PCA as the preferred method can decisively be made.

5.5 Possibility for further improvement

5.5.1 Experimental Setup

It is important to note factors influencing data recorded during the experiments. These factors must be addressed in future work in order to create a system that is replicable and sustainable.

Notable issues experienced by subjects include:

- Subject 1, 5 and 9 revealed they found it difficult to stop shaking while breathing (this may have been due to the chin rest);
- Excessive amounts of blinking were experienced by subjects 2 and 15; and,
- Subject 6 experienced KCl solution dripping into his eyes from the application of the GSN net.

Additionally external factors affecting recorded data must be addressed if possible:

- Certain subjects had to be tested in the evening; hence the lights were left on in the recording room. This can produce high frequency interference with the EEG which contradicts the testing requirements stipulated by Luck (2005). Every attempt must be made for testing subjects at the same time of day to ensure the only variable contributing to EEG changes is the paradigm.
- Additionally the size of the GSN net and the positioning thereof are crucial in recording data with integrity with regards to scalp topography and impedance.

- Earphones can cause high frequency interference in channels located near the ear in high resolution systems.

5.5.2 Experimental paradigms

Probability of the P300 should be addressed as a means of improving the target P300 waveform generation. A balance needs to be created between increasing selectivity (i.e. number of input options) and therefore decreasing probability of target stimuli, and task difficulty in distinguishing between stimuli. This problem lies more with auditory stimulus generation as opposed to visual stimulus presentation.

Button pushing revealed no improvement, if not less accurate in certain experiments, than silent counting. This bodes well for clinical implementation where button pushing isn't an option for patients suffering from serious neural disorders.

The lack of attention (evident from the difference in count verification for certain subjects in Appendix K) can attenuate the target P300 amplitude and further decrease the classification accuracy.

It is also imperative that counterbalancing is taken into account in an attempt to mitigate the overall group results affected by habituation and/or fatigue.

5.5.3 Auditory versus visual stimuli

Although visual stimuli, in general, provide better classification results, the fact that ALS patients (and certain subjects in this research) perform better using auditory stimuli, provides scope for its implementation in future FES-BCI systems.

A notable aspect for P300 paradigms that should be addressed is creating external stimuli which are easily distinguishable amongst each other (especially in multi-class paradigms were task difficulty is increased). This will enable the user to identify target stimuli with confidence and require fewer data trials for classifier training.

5.5.4 Signal processing

Due to the saliently high classification results obtained by PCA (in some cases 100% accuracy – see Table 4.2), the possible incremental improvement in accuracy, sensitivity, specificity, PPV, and NPV could only be negligible due to the already accurate results obtained by PCA. The literature additionally supported the use of PCA for data reduction prior to ICA due to the computational complexity of computing ICA algorithms across all channels. However, the author acknowledges that further work can be conducted into investigating ICA alone as an alternative signal processing technique.

Asynchronous solutions need to be explored for FES P300 BCI systems. The algorithm should be tested in an online state to determine its effectiveness for real-time application. It has been shown that online classification performance may be significantly lower compared with offline performance analysis. This is due to training and testing the model with data from the same time interval rather than new 'unseen' data from each subject. This decrease in performance can be due to a lack of focus. Additionally factors such as noise and the state of the observer can be manipulated in the offline state ultimately distorting classification results (Muller-Putz et al. 2006). The method of PCA and ICA with time and space manipulation of the controlling waveform is not an effective means of improving classification accuracy for the adopted paradigms. PCA alone proves a better option for signal processing if the target waveform is robust and easily distinguishable from other EEG outputs.

The 'real' environment performance of a BCI can be enhanced by the number of factors retained by PCA reduction or equivalently by using a low resolution system with fewer channels. Alternative classifiers can be explored to determine the best categorisation method for the proposed paradigm and signal processing techniques.

Additionally, due to the blanket use of the same feature selection parameters and C-value (SVM classification) across all the subjects and paradigms, the classification accuracy could be improved by determining the best discernible feature set and C-value for each individual subject or paradigm.

6 Conclusion

Based on the findings of this research, the following conclusions are drawn against the objectives specified:

1. **The proposed multi-class paradigm presents a feasible P300 paradigm for increased selectivity**

The classification accuracies obtained were comparable, although less accurate, than the traditional paradigm. However, the added benefit of increased user selectivity makes it an attractive option as a step towards FES application. Certain enhancements can be made to the paradigm to improve the categorisation accuracy; however this may limit other elements of the paradigms functionality. For example, by decreasing the probability of target inputs, the accuracy may improve; however, the 'real' environment applicability is negated because one option (or selection) will then be favoured above the rest. In other words, the proposed paradigm presents the subject with a choice of three targets (T1T2T3). After target selection the other two targets become standard stimuli (e.g. if T1 was chosen the paradigm becomes T1S1S2) and have equal probability i.e. no matter which target is chosen. If that probability is changed and 'favoured' (or rather 'not favoured') towards one of the stimuli (e.g. T1T2T2T3T3), the 'real' environment applicability of the paradigm is lost because that stimulus will always be favoured as the target due to its decreased probability.

2. **An auditory stimulus modality presents a viable alternative to the visual stimulus for 'real' environment applicability**

Although, in general, the accuracies obtained by visual stimulus paradigms proved superior, the differential margin in categorisation accuracy was diminished with the improved signal processing techniques. Additionally, the added benefits of auditory stimuli presentation discussed in the literature, provides emphasis for its potential applicability in FES. Thus visual stimuli paradigms did not outweigh auditory stimuli paradigms as an overall advantage for FES-BCI systems.

3. **Using a combination of PCA for data reduction, ICA for P300 source extraction, and P300 temporal and spatial enhancement signal processing techniques, did not improve classification accuracies for the experimental paradigms that were developed, however utilising PCA alone vastly improves the classification accuracy**

By using PCA as a data reduction technique before ICA, the accuracy was worsened. This is unexpected and the reason for this is unclear (requiring further investigation). This may be due to the manner in which ICA was implemented e.g. different ICA algorithms could have been implemented and compared to each other with regards to performance improvements of the accuracy. Although theoretically the amount of data may be improved through this reduction technique before ICA, it is negated by the fact that PCA alone performed vastly better as a signal processing tool for the paradigms that were developed. Data reduction proves especially important in high-resolution systems where vast amounts of channels are recorded. The apparent benefit of P300 enhancement through temporal and spatial manipulation did unfortunately not enhance the predictive accuracies for single-trial classification of these paradigms.

7 Recommendations for further research

Based on the findings and conclusions of this research, the following recommendations for further developments are made:

1. **Investigate the use of a low resolution EEG system**

The high resolution Geodesic Sensor Net is extremely cumbersome and only suitable for research. To ensure realistic applicability, a low resolution system should be tested for accuracy and aesthetic appeal. Additionally the speed of classification can be realistically measured due to the reduced number of channels compared with the high resolution system.

2. **Examine FES application of the proposed system**

The ultimate aim was to create a P300 BCI module that could effectively control an FES based system. The applicability of which could be tested on existing FES designs.

3. **Investigate the real-time online response speed and accuracy of the proposed signal processing technique**

The ultimate goal would require the system to respond online to single-trial P300 after subject and classifier training.

4. **Enhancement of the proposed multi-class paradigm**

Different use of tones, response techniques, experimental setups, and hardware may result in more accurate and promising 'real' environment applicability. Additionally by decreasing the probability of the target stimulus the

P300 amplitude will be improved. However, this does impact the use of online BCI paradigms because one stimulus will be favoured.

5. **Create an asynchronous P300 BCI**

By using a system such as Mind Switch to turn synchronous systems on/off, an online P300 BCI can be created using the proposed paradigms. The offline approach results in manual artefact rejection which means a loss of data. An online approach would represent a more 'real' application.

6. **Use tones of varying length rather than frequency**

This method was explored by Schreuder et al. (2010) and may improve the user's ability to distinguish between stimuli and hence improve the overall accuracy of the system.

7. **Increasing the number of selection or target options**

According to the P300 characteristics, by decreasing the probability of the target the amplitude is improved. Hence by increasing the number of inputs, the chosen target stimulus probability will decrease and possibly increase the amplitude of the target P300. However, conversely the P300 is affected by increased task difficulty and this may negatively attenuate the P300 amplitude.

8. **A phase controlled FES system, similar to the paradigm employed by Pfurtscheller et al. (2003 and 2005), but utilising a P300 approach**

By utilising the traditional P300 paradigm as the control method, but additionally employing phase control, an online FES BCI could be created. The target P300 could be used as a 'switch' to push the FES system through phases of performing a functional movement.

9. **Investigate means of improving the bit rate for 'real' environment applicability**

The performance of a BCI system is measured by its information transfer rate in bits/min or commands/min (McFarland, Sarnacki & Wolpaw 2003). The bit rate employed by various FES-BCI systems is still relatively slow. By further improving the signal processing steps, decreasing the number of channels, or enhancing the control paradigm, this bit rate may be improved.

10. **Investigate the use of alternative classifiers**

NNs and LDA classifiers present alternative means of target categorisation. These may improve the speed and accuracy of the proposed P300 BCI paradigms.

11. **Investigate the use of ICA alone as a signal processing step for classification**

ICA's ability to extract source signals from signal mixtures provides an attractive means of extracting the P300 features in noise.

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Appendix A Brain-Computer Interface

EEG ultimately provides a means of communication between man and machine via a BCI (see Appendix B for an explanation of EEG). "The principle of BCI control is that a person can voluntarily change, or learn to change, neuronal activity in their brain" (Pfurtscheller et al. 2003). Advances in technology have allowed EEG to be analysed in real-time opening vast possibilities for clinical research. BCI research includes non-invasive approaches using standard scalp electrodes and invasive approaches that use cortical or depth recording (Wolpaw et al. 2002). Invasive recording techniques require implants into the grey matter of the brain. They produce the highest quality signals but are prone to scar-tissue build-up (the body may react against the foreign matter if used for long periods).

The BCIs communication operates by sending signals to or accepting commands from the brain[33] (Levine et al. 2000). BCIs "determine the intent of the user" from various EEG signals in the brain[34] - visual-evoked potentials (VEPs), cortical and P300 potentials, μ and β rhythms, and cortical neuronal activity (Wolpaw et al. 2002) - and translate these into real-time responses that operate a variety of devices.

The core element of each BCI is a "translation algorithm that converts EEG biopotentials from the user into an output signal that controls an external device" (Sinkjaer et al. 2003). The symbiotic operation of a BCI depends on the interaction between two adaptive controllers, "the user who encodes his or her commands in the EEG input provided to the BCI, and the BCI, which recognises the commands

[33] The ability for a two-way BCI to operate effectively is at this stage extremely limited and thus there is continued research in this field.
[34] BCIs may be used with non-invasive EEG or invasive approaches that record cortical or depth activity in the brain (Wolpaw et al. 2002).

contained in the input and expresses them in the device control” (Sinkjaer et al. 2003). This enables the feasibility of FES-BCI systems.

Scalp EEG BCI systems can be classified in either of the following groups:

- VEPs – EEG potentials measured at the visual cortex produced by visual stimuli;
- P300 ERPs – an inherent response to auditory, visual, somatosensory or task relevant stimuli;
- SCPs – slow potential shifts of the EEG in the cortex (with training these can be regulated); and,
- Mu (µ) and beta (β) rhythms – spontaneous EEG activities at the sensory motor cortex when not engaged in processing inputs or outputs.

BCIs are also grouped into dependent and independent classes. A dependent BCI does not use the normal output pathway of the brain to convey information, but the activity in those pathways is needed to generate changes in the EEG (Wolpaw et al. 2002). These are detected by the computer and translated into messages. An independent BCI using brain activity directly to send information does not rely on the normal pathways or activity within them. Hence, they provide a direct channel between man and machine (a crucial requirement for people suffering from CLIS).

It should be noted, however, that inter-subject variability exists in EEG and various methods may need to be tested to ascertain which provides the best control.

A general BCI consists of the modules shown in Figure A.1.

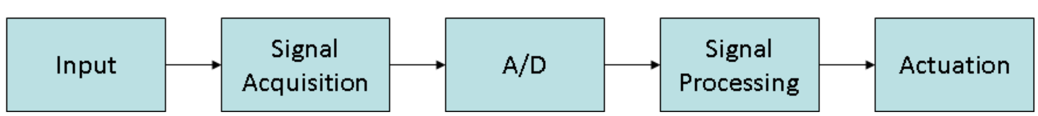

Figure A.1 The modules included in a general purpose BCI.

A common thread throughout BCI research is the remarkable cortical plasticity of the brain, which is able to treat neuroprostheses (or FES) controlled by BCIs as natural limbs to some extent. With advances in technology and knowledge, researchers could now conceivably attempt to produce BCIs that augment human functions rather than simply restoring them.

Appendix B Underlying Principles of EEG and ERP

B.1 Electroencephalography (EEG)

Electroencephalography is the measurement of electrical activity of the brain recorded by electrodes placed on the scalp (invasively or non-invasively). It is a graphical representation of the difference in voltage between electrodes (usually a 'reference' electrode) (Olejniczak 2006).

EEG originates from synaptic activity of neurons inside the cortex[35]. The electric potentials can be measured as EEG when thousands of these neurons interact synchronously. The resultant volume conduction causes distribution of potentials to spread across the scalp. EEG is therefore a two-dimensional projection of three-dimensional activity in the brain (Olejniczak 2006).

It should be noted that eye blink and eye movement (EOG), muscle movement (EMG), sweating, electrical interference, bad electrode contact and movement of wires all produce artefacts in EEG recordings (Fatourechi et al. 2007). These are potential shifts that do not originate from the brain[36]. It is essential that artefacts aren't mistaken for EEG when analysing data.

B.2 Event-Related Potential (ERP)

An event-related potential is any electrophysiological response in the brain to an external or internal stimulus. These are cognition responses relating to a thought or perception (Picton 1992). These patterns in the brain may be recorded

[35] Electrochemical signals cause neurons to become polarised and depolarized,

[36] There are two categories: artefacts that arise from physiological movement and electrophysiological sources inside the body; and artefacts that arise from noise and interference outside the body.

by EEG and revealed using averaging techniques. This provides an easy and simple method of analysing robust ERP (e.g. P300) signals in EEG. Simplified, an ERP is a set of voltage changes contained within an epoch[37] of EEG that is associated with some time dependent event. The changes are often small in relation to the rest of the EEG in which they are embedded. Thus signal processing techniques are employed to 'extract' the signal from the noise. Recording a number of epochs, which are time-locked to repetitions of the same event, and averaging them for each time-point in the epoch yields a vector of values representing the average activity. This is the average ERP. The assumption is that activity not time-locked to an event will vary randomly across the epoch and tend to be averaged to zero. The residual waveform should therefore largely represent activity in the brain that correlates to a fixed temporal relationship with that of the event being investigated (Coles, Rugg 1996).

However, it does require much computational power on the part of a BCI to employ an averaging technique. It can also not provide a direct estimate of the ERP elicited by individual events. Furthermore, the average waveform may sometimes not resemble the actual waveform that is recorded on an individual trial[38]. Defining and extracting ERPs have certain impediments, such as component overlap and the ambiguity surrounding the peaks and troughs[39] (Coles, Rugg 1996). This translates to the fact that it provides an inefficient and inaccurate method of performing single-trial detection – the ultimate aim of high-powered BCIs.

[37] An epoch represents a time-locked event frame of EEG.
[38] This occurs if the amplitude or latency of a waveform has bimodal distribution.
[39] For example, an ERP with a latency of 300 ms, may reflect the combined activity of two or more neurons which are maximally active before and after 300 ms, but with fields that summate to a maximum.

Appendix C Recording Biopotentials from the Brain

EEG signals for BCIs are typically recorded at several sites correlating to the relevant brain regions being monitored. These systems can use different principles from the natural rhythms or spontaneous EEG (activity not tied to a specific evoking stimulus)[40] (Sinkjaer et al. 2003). The EEG correlates brain functions (or dysfunctions) and requires signal processing techniques (e.g. spectral analysis) to evaluate.

The EEG appears as rhythmical signals due to its oscillatory characteristics and can be classified into five rhythms according to their frequency range: alpha, beta, theta, delta, and gamma. Table C.1 summarises these rhythms, which are illustrated in Figure C.1.

[40] For example, event-related synchronisation (ERS) and desynchronisation (ERD) dependent on movement associated EEG.

Table C.1 Types of brainwaves with their associated mental state (summarised from Webster (1998)).

Brainwave	Frequency Range	Associated Mental State
Delta	0 – 4 Hz	deep sleep
Theta	4 – 7 Hz	drowsiness, light sleep
Alpha	8 – 13 Hz	relaxed, calmed, alert state consciousness
Beta	14 – 30 Hz	active, busy, anxious, thinking, concentrating
Gamma	+40 Hz	higher mental activities

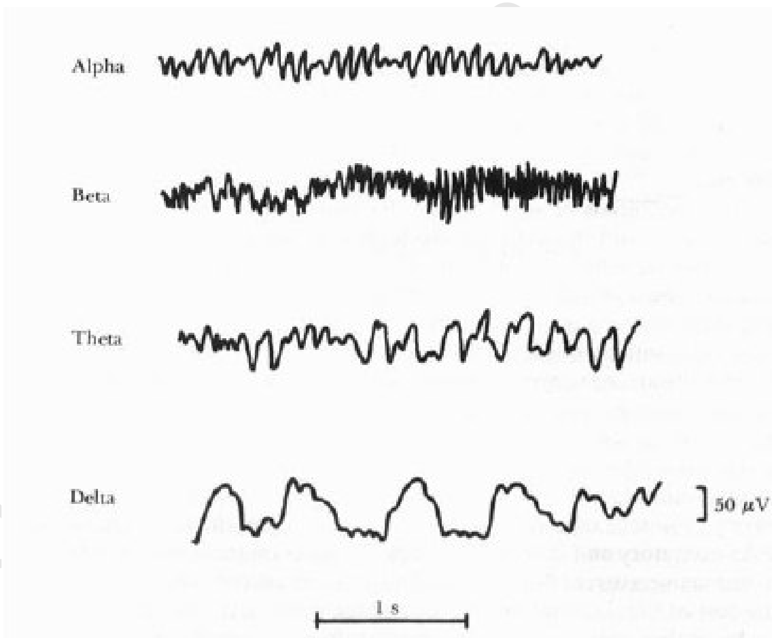

Figure C.1 Brainwave component frequencies (Webster 1998).

C.1 EEG Hardware

A typical recording system is seen in Figure C.2 (Teplan 2002).

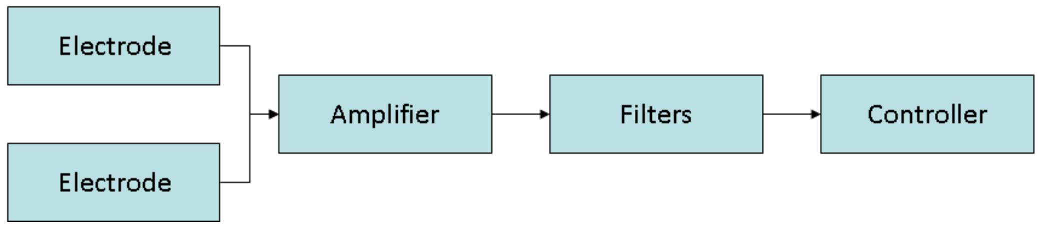

Figure C.2 The modules associated with EEG recording.

The electrodes (disposable or permanent) are typically mounted according to the international 10–20 system (see Appendix E Figure E.1). EEG is recorded monopolarly against a reference, bipolarly between two active scalp electrodes, or against a common value (average of the rest of the electrodes) typically with a differential DC-coupled amplifier (EEG signals are weak – approximately 20 to 100 µV - and have high source impedance) with a gain in the range of 500 – 10000. The differential amplifier must have high common-mode rejection ratio (at least 100 dB) and high input impedance (at least 100 MΩ) in order to minimise loading effects and the distortion of the signal (Teplan 2002). The relevant frequency range is from DC to 100 Hz, and the EEG is normally sampled at 500 Hz or less using a resolution of 12 – 16 bits (Sinkjaer et al. 2003).

Low pass filters remove 50/60 Hz electrical noise. A notch filter can be used to remove this noise if the frequencies of interest are above 50/60 Hz (although this can result in phase distortion). The controller determines the sampling rate at which to repeatedly sample data at fixed time intervals from the analog signal and thus converts the information to a digital signal by means of an analog-to-digital (A/D) converter. The resolution of the system is determined by the smallest amplitudes that can be sampled. The controller/converter then interfaces with a recording device (display or storage).

Appendix D P300

Electrical activity in the brain associated with passive or active movement of extremities has to some degree an effect on the integrity of the EEG signal recordings. Other EEG signals need to be investigated that may act as a control signal but are not impacted or produce negative feedback as a result of extremity movement. One such brain waveform is that of the P300.

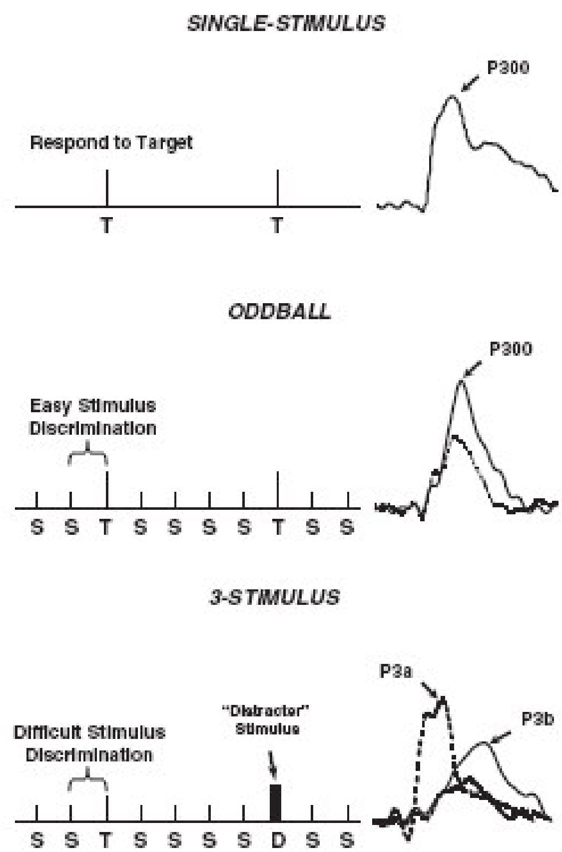

Figure D.1 Schematic illustration of the P300 waveform (Polich, Criado 2006).

A P300 BCI uses a specific brainwave called the P300 as its decision medium. It is an ERP component of the EEG and indicates a subject's recognition of useful target information according to a task. The P300 (or simply P3) is one of the most robust features of an ERP (Sutton et al. 1965). In Figure D.1, the single-stimulus task, the target (T) is presented at random intervals eliciting a P300. In the OP the target is presented infrequently and randomly amongst other standard stimuli (S). And in the three-stimulus task the target is presented infrequently with standard stimuli and a distracter stimulus (D). The target elicits a large positive going potential that increases in amplitude from the frontal electrodes of an EEG to the parietal electrodes (Polich, Criado 2006).

The P300 is a stimulus in the frontal-central-parietal region of the brain that appears as a positive deflection of the EEG voltage at approximately 300 ms. The reason it peaks at 300 ms is due to the latency of context updating. The context updating hypothesis states that "it reflects an updating of expectancies about how probable events are in the current context. Because this updating cannot be conducted until the stimulus has been categorised, its latency is dependent on how long it took to come to a decision" (Navratil, Ramabhadran 2009). Therefore this time can vary depending on the difficulty of the target discrimination. The P300 latency reflects only the stimulus evaluation or perception time and not the time it takes to then convert the decision into a physical response (Navratil, Ramabhadran 2009).

P300 waves are also distinguishable in oddball stimuli when a target is recognised to be different to anything else. This is important in establishing renewed interest in a stimulus or series of stimuli. The P300 indicates a subject's ability to identify, categorise and update 'working memory' with new or required information.

An important concept of the P300 is also its inverse relationship with the probability of an oddball stimulus. The amplitude is greater for a less frequent target as opposed to a smaller amplitude for a more frequent target. Although the P300 is still present the frequency has a direct response on the recorded 'spike' (Picton 1992). Rarity and categorising are two parameters that influence the amplitude of the P300. This correlates to the larger the amplitude, the more important the target. It is useful to BCI application because it only becomes noticeable in EEG when the subject is actively tracking the stimulus, therefore giving information as to what they are paying attention to (Sutton et al. 1965).

The P300 consists of two subcomponents: the novelty P3, or P3a[41], and the classic P3, or P3b[42]. "The P300 brain potential can provide information about cognition that is quantitatively comparable to other clinically used biomedical assays" (Polich 2004). The reasons surrounding P300 variability with respect to task and biologic determinants are well understood so that refinement of ERP methods for clinical applications is possible. It is important to note that elaboration of how P300 and other ERP components reflect neuropsychologic processes would help to increase their clinical relevance. "In particular, development of reliable P3a paradigms used in conjunction with P3b tasks promises to augment dramatically the applicability and sensitivity of ERPs. Use of P300 as a clinical evaluation tool should be revisited with contemporary theory, methods, and analysis procedures because a reliable neuroelectric measure of mental function would redefine the assessment of cognitive disorders" (Polich 2004).

There are numerous ongoing processes that aren't visible in EEG, but the brain's electrical response to a target (T) stimulus manifests in a 'positive deflection' in voltage that can be processed[43]. This deflection can realistically only be seen after many recordings have been averaged, which would cancel out the noise (biological and ambient).

P300 signals form a basis whereby BCIs are able to decode categories of thoughts. The signal waves are generated involuntarily when individuals see something they recognise as a target. This method has an advantage of not

[41] The less frequent or rare targets elicit a positive-going potential which occurs between 220 ms and 280 ms. This occurs at the frontal midline sites.
[42] This is a positive-going potential at the parietal midline sites between 310 ms and 380 ms when infrequent targets are attended to.
[43] Note that EEG operates on signals of amplitude tens of microvolts.

requiring as much training of patients compared with other techniques used. “The P300 wave may represent the transfer of information to consciousness, a process that involves many different regions of the brain” (Picton 1992). This indicates that because of the processes generated intracranially by the waveform, the need to target a specific location is suppressed. Detection and depiction probabilities are thus enhanced by the wave’s anatomical progression in the cerebrum.

The problem with using a P300 event-related BCI is that is allows only a binary output of information. The P300 is either present or it is not, indicating the limitations of the interface design. Thus other methods using different electrical activity responses in the brain present a wider range of selective techniques (such as μ or β waveforms), but the integrity error ratios are greatly increased due to resolution requirements and variations in waveform response[44]. The P300 wave, although limited by its ‘yes or no’ capability, has the added benefit of being a noticeable fluctuation in cerebral activity and is relatively generic in time, space and amplitude. This creates the potential for single-trial P300 BCIs with as little training as possible.

Allowing people, who are partially or completely locked-in through paralysis or degenerative neural diseases, to communicate with their environment without requiring the need for functional use of peripheral nerves and muscles has a major impact on their quality of life.

[44] The ultimate BCI goal is for integrity of selection and hence the importance of using a robust technique.

Appendix E Electrode Nomenclature and Montages

The 10-20 electrode placement system uses known neuro-anatomical landmarks for determining the reference points. The electrodes are placed at 10% and 20% of the distance from the reference points (Klem et al. 1999) equating to 21 electrode positions. The naming convention of the electrode locations matched the underlying anatomy: Fp – pre-frontal, F – frontal, P – parietal, T – temporal, C – central, O – occipital, and ‘z’ refers to electrodes placed at the midline. Additional electrodes (placed between these electrodes) for higher resolution systems followed this naming technique. Figure E.1 illustrates the naming convention for the 10-20 system.

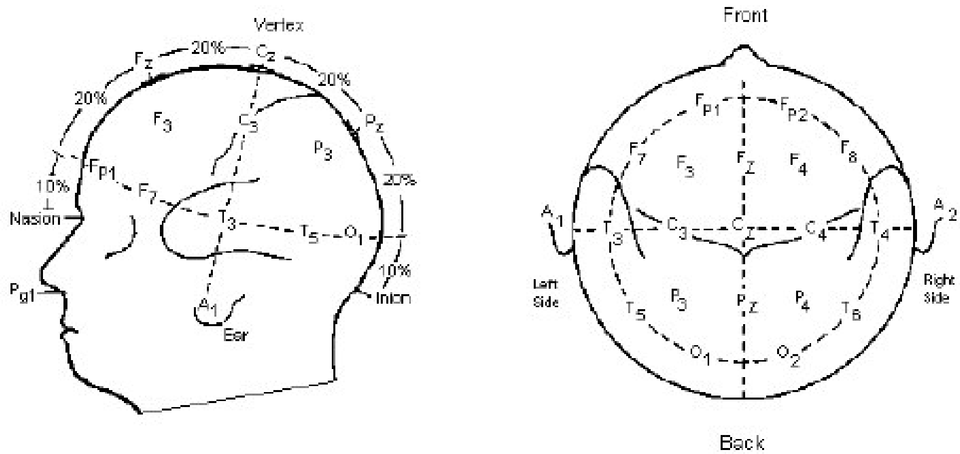

Figure E.1 10-20 International system of electrode placement (UW Technology 2009).

The advancement of multi-channel EEG hardware and topographic methods resulted in the 10-20 system being extended to 10-10 (or 10%) representing 74 electrode placements and eventually to a 5% system representing 345 positions (Oostenveld, Praamstra 2001). Currently, laboratories use 32, 64, 128, and 256 channels when studying EEG. The arrangement of electrodes is known as a montage, of which there are three types:

- Bipolar – electrodes are arranged in pairs and each channel measures the potential difference between these electrodes.

- Monopolar – the potential difference between each electrode and a common ‘reference’ electrode are measured (the ‘reference’ electrode usually has the least relevant activity). Selection of the ‘reference’ electrode is important as EEG distortion may result if the channel has high activity.

- Reference free montage – the potential difference between each electrode and a common value (calculated from the rest of the electrodes) is measured. However, this montage may be affected by amplitude artefacts causing signal distortion over the common value.

Appendix F Geodesic Sensor Net Specifications

The following specification is an extract from the GSN technical manual (Electrical Geodesics 2001).

F.1 Overall System Specifications

System 200 has been designed for use under the environmental conditions given in Table F.1.

Table F.1 GSN system 200 overall operating environment.

Storage temperature	0° to 47° C (32° to 116° F)
Operating temperature	10° to 35° C (50° to 95° F)
Relative humidity	5% to 95% non condensing
Maximum altitude	3048 m (10000 ft)

F.2 Dimensions and Weight

The following are approximate overall dimensions for the Net Amps box:

- Height: 27.9 cm (11 inches)
- Width: 43.2 cm (17 inches)
- Depth: 48.0 cm (18.9 inches)

The approximate weight of the Net Amps box is 16.8 kg (37 lb).

F.3 Dynamic Range

Maximum resolvable signal is ±2.5V/1000, or ±2.5 millivolts.

F.4 Precision

Minimum resolvable signal is ±2,500/32,768, or 0.076 microvolts.

F.5 Inherent Noise

Amplifiers always have a certain amount of low-level noise inherent to the circuitry. This noise comes from a variety of sources, including thermal activity, leakage of digital signals to analog circuitry, and power supply noise. The Net Amps is a low-noise amplifier: Net Amps internal noise, measured with the analog inputs grounded, is tested to be less than 1 µV RMS, and typically falls below 0.6 µV RMS. Amplifier inherent noise is to be distinguished from noise that has an environmental origin.

Appendix G E-prime

A program developed in E-prime was used to present the subjects with each experiment. Subjects were presented with instructions relating to each paradigm which included an initial presentation of the target stimulus (randomly chosen for each subject) and information regarding limiting as much movement as possible i.e. blinking, breathing, and extremity movement.

The targets randomly chosen for each subject are shown in Table G.1 and a screenshot of the program developed in E-prime is shown in Figure G.1.

Table G.1 Targets randomly chosen by E-prime for each experiment. * = with button pushing, ** = with silent counting. Subjects were also additionally asked to rate their level of fatigue after the experiments on a scale of 1 to 5.

Subject	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Fatigue
	Auditory Multi-class**	**Auditory Multi-class***	**Visual Multi-class****	**Visual Multi-class***	**Traditional***	***Scale 1-5***
1	1500 Hz	500 Hz	→	←	↓	2
2	3500 Hz	1500 Hz	↑	→	3500 Hz	4
3	1500 Hz	500 Hz	←	←	↓	2
4	1500 Hz	1500 Hz	←	←	3500 Hz	5
5	1500 Hz	3500 Hz	←	→	↓	3
6	500 Hz	3500 Hz	→	↑	3500 Hz	2
7	1500 Hz	500 Hz	←	←	↓	5
8	3500 Hz	3500 Hz	←	←	3500 Hz	3
9	3500 Hz	3500 Hz	↑	→	↓	3
10	500 Hz	500 Hz	↑	←	3500 Hz	4
11	500 Hz	3500 Hz	←	↑	↓	1
12	3500 Hz	1500 Hz	→	↑	3500 Hz	5
13	1500 Hz	500 Hz	←	←	↓	2
14	1500 Hz	1500 Hz	↑	←	3500 Hz	2
15	500 Hz	1500 Hz	→	↑	↓	1

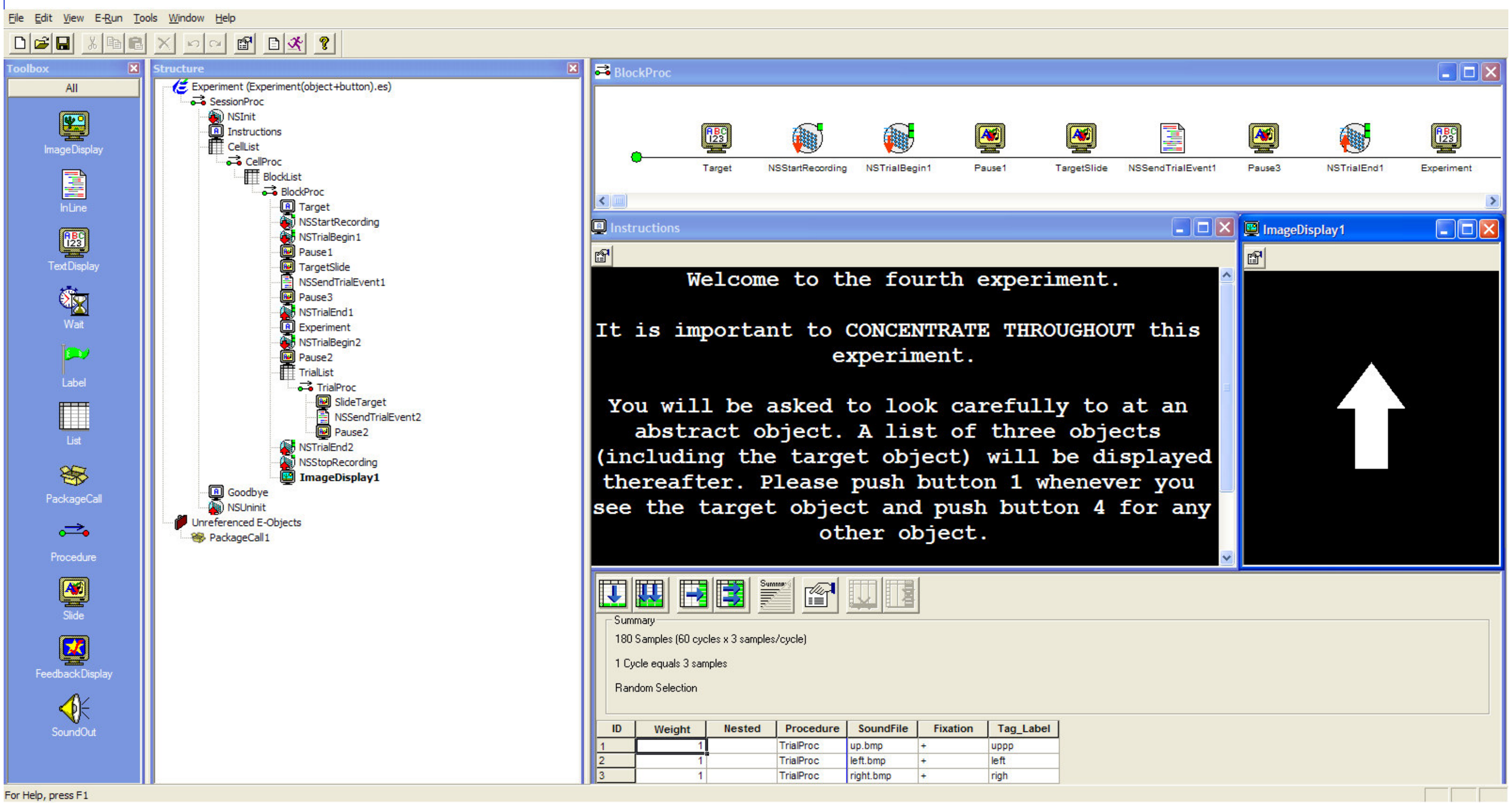

Figure G.1 Screenshot of paradigm 4 as an example of the E-prime program developed to present the subjects with the different experiments.

Appendix H Example of Pre-Recording Questionnaire

<u>Experiment Sheet</u>

Date: ______________________________

Name: ______________________________

Age: ______________________________

Right-handed: ☐ Yes ☐ No

Gender: ______________________________

Hearing/Vision Impairment: ______________________________

Neurological Disorder: ______________________________

Last Ate: ______________________________

Oral Temperature: ______________________________

Medication: ______________________________

Alcohol/Smoking: ______________________________

<u>Experiment 1</u>

Target: ______________________________

Number of targets: ______________________________

<u>Experiment 2</u>

Target: ______________________________

Number of targets: ______________________________

<u>Experiment 3</u>

Target: ______________________________

Number of targets: ______________________________

<u>Experiment 4</u>

Target: ______________________________

Number of targets: ______________________________

Appendix I Ethics Approval

UNIVERSITY OF CAPE TOWN

Health Sciences Faculty
Research Ethics Committee
Room E52-24 Groote Schuur Hospital Old Main Building
Observatory 7925
Telephone [021] 406 6492 • Facsimile [021] 406 6411
e-mail: Nosi.Tywabi@uct.ac.za

18 December 2007

REC REF: 449/2007

Mr ASJ Bentley
C/o Dr L John
Human Biology

Dear Mr Bentley

PROJECT TITLE: AN OFFLINE AUDITORY P300 BRAIN-COMPUTER INTERFACE USING PRINCIPAL AND INDEPENDENT COMPONENT ANALYSIS TECHNIQUES FOR POTENTIAL CONTROL OF A FUNCTIONAL ELECTRICAL STIMULATION SYSTEM.

Thank you for submitting your study to the Research Ethics Committee for review.

It is a pleasure to inform you that the Ethics Committee has **formally approved** the above mentioned study.

This serves to confirm that the University of Cape Town Research Ethics Committee complies with the Ethics Standards for Clinical Research with a new drug in patients, based on the Medical Research Council (MRC-SA), Food and Drug Administration (FDA-USA), International Convention on Harmonisation Good Clinical Practice (ICH GCP) and Declaration of Helsinki guidelines.

The Research Ethics Committee granting this approval is in compliance with the ICH Harmonised Tripartite Guidelines E6: Note for Guidance on Good Clinical Practice (CPMP/ICH/135/95) and FDA Code Federal Regulation Part 50, 56 and 312.

Please note that the ongoing ethical conduct of the study remains the responsibility of the principal investigator.

Please quote the REC. REF in all your correspondence.

Yours sincerely

Lesley Henley

pp PROF M BLOCKMAN
CHAIRPERSON, HSF HUMAN ETHICS

lem jedi

Appendix J Subject Consent Form

An Offline Auditory P300 Brain-Computer Interface using Principal and Independent Component Analysis Techniques for potential control of a Functional Electrical Stimulation System

Informed consent

Researchers at the MRC/UCT Medical Imaging Research Unit are investigating the possibility of using different mathematical techniques of analysing recognition tasks recorded by EEG to allow a Brain-Computer Interface (BCI) to control an electrical device. A P300 waveform is generated in the brain with a person's recognition of useful information. This signal provides a means of acting as a control device for a BCI. The P300 is recorded using EEG. EEG is a safe non-invasive recording technique and requires the placement of a net of sponge covered electrodes on the head of a participant.

Testing procedure

All testing will be carried out at the UCT Faculty of Health Sciences, and has been pre-approved by the Human Ethics committee. You will be required to wash your hair with shampoo prior to testing. Participants will be seated in a chair facing a computer monitor, and will be fitted with a high resolution EEG net and headphones – see figure D1. A series of recognition tasks will be presented using the computer monitor and headphones. Testing should take approximately 1 hour. You will be paid R50 on successful completion of the recording.

Participant with EEG recording net.

Possible risks associated with participation

The EEG equipment is inherently safe. Temporary mild skin sensitivity may result from the salt solution used with the electrode sponge. In the unlikely case of any subject experiencing discomfort, the subject should alert the investigator. The University of Cape Town has a public liability cover should some unforeseen event occur whilst you are participating in this study.

Statement of understanding and consent

I confirm that I am over 21 years of age, and the exact procedure and techniques and the possible complications of the above tests have been thoroughly explained to me. I am free to withdraw from the study at any time should I choose to do so. I understand that I may ask questions at any time during the testing procedure. I know that the personal information required by the researchers and derived from the testing procedure will remain strictly confidential and will only be revealed as a number in classification analysis. I have carefully read this form and understand the nature, purpose and procedures of this study. I agree to participate in this research project conducted by the MRC/UCT Medical Imaging Research Unit.

Name of volunteer / guardian (if necessary):____________________

Signature:____________________

Name of investigator:____________________

Signature:____________________

Date:____________________

Research Team

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Appendix K Count Verification and Channel Removal

Table K.1 Count verification and channel removal - outliers are highlighted in RED (*diff.* = difference).

Expt.	**1**	**Verification**	**3**	**Verification**	**1**	**2**	**3**	**4**	**5**
Subject	**Hz**	***target* (*diff.*)**	**Arrow**	***target* (*diff.*)**	**Channels Removed Per Experiment**				
1	1500	60 (0)	→	63 (3)	0	2	6	8	10
2	3500	65 (5)	↑	61 (1)	4	1	0	1	0
3	1500	60 (0)	←	61 (1)	11	5	7	2	22
4	1500	56 (4)	←	62 (2)	0	1	3	26	1
5	1500	58 (2)	←	60 (0)	1	0	0	0	20
6	500	59 (1)	→	59 (1)	0	0	0	0	0
7	1500	71 (11)	←	61 (1)	17	5	2	2	3
8	3500	61 (1)	←	60 (0)	3	4	4	1	3
9	3500	60 (0)	↑	60 (0)	23	13	0	8	0
10	500	60 (0)	↑	65 (5)	35	28	32	12	11
11	500	59 (1)	←	60 (0)	27	13	0	0	0
12	3500	62 (2)	↑	60 (0)	16	3	10	34	2
13	1500	61 (1)	←	60 (0)	0	1	0	1	1
14	1500	59 (1)	↑	52 (8)	2	11	6	7	3
15	500	60 (0)	→	59 (1)	2	4	0	5	9

Appendix L Data Analysis MATLAB Code

This section contains the MATLAB code used for data analysis of the EEG. The files include:

- Perform analysis on recorded EEG
- Extract and pre-process all ERPS from the raw data
- Extract separate epochs from the concatenated data
- Calculate the moving average under the curve for successive periods of each channel
- Temporal and spatial manipulation
- Temporal manipulation
- Spatial manipulation
- Perform PCA
- Feature Selection
- Thornton's Separability Index (GSI)

L.1 Perform analysis on recorded EEG

```
function performanalysis()
% performanalysis - performanalysis() - perform full
% analysis on recorded EEG including normal extraction, PCA ICA extraction,
% PCA ICA with spatio-temporally manipulated components, and PCA
% extraction.

% outputs are saved to file

clc
clear all
close all

ques = input('Would you like to do a single experiment extraction or a full extraction (single or full)? ', 's');

if strcmp(ques,'single')
    % obtain extraction details from user
    NUM_FAC = input('How many factors would you like to retain? ');

    file = input('What is the file name? ', 's');
    % for plotting
    channel = input('Choose a channel to view (1 -> 129): ');
    target = input('What is the target event? ', 's');
    ques = input('How many non-target events are there (0,1 or 2)? ');
    if ques == 1
        nt1 = input('What is the non-target event? ', 's');
        nt2 = 'none';
    elseif ques == 2
        nt1 = input('What is the first non-target event? ', 's');
        nt2 = input('What is the second non-target event? ', 's');
    elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
        error('Incorrect entry!');
```

```
else
    nt1 = 'none';
    nt2 = 'none';
end

compute_laplac = input('Would you like to compute a surface laplacian (Y or N)? ', 's');

trials = [];
ques = input('Which trials would you like to remove (0 = none)? ');
if ques == 0;
    trials = [];
else
    trials = cat(2,trials,ques);
    ques = 1;
    while ques ~= 0
        ques = input('Which other trials would you like to remove (0 to end)? ');
        trials = cat(2,trials,ques);
    end
end

% perform pre-processing
filtereddata = extractallERPsfromrawdata(file,target,nt1,nt2,compute_laplac,trials);

% extract separate epochs
[target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-ICA',target,nt1,nt2,NUM_FAC);

targetn = movingaverage(target1n);
nt1n = movingaverage(xnt1n);
if strcmp(nt2,'none')
    nt2n = [];
else
    nt2n = movingaverage(xnt2n);
    nt2n = nt2n(:,6:20,:);
```

```
    end
    targetn = targetn(:,6:20,:);
    nt1n = nt1n(:,6:20,:);

    % performs extended ICA extraction with weighted Varimax PCA data reduction
    [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',target,nt1,nt2,NUM_FAC);

    targetICA = movingaverage(target1ICA);
    nt1ICA = movingaverage(xnt1ICA);
    if strcmp(nt2,'none')
        nt2ICA = [];
    else
        nt2ICA = movingaverage(xnt2ICA);
        nt2ICA = nt2ICA(:,6:20,:);
    end
    targetICA = targetICA(:,6:20,:);
    nt1ICA = nt1ICA(:,6:20,:);

    % spatio-temporally manipulates independent components
    [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

    targetICAmanip = movingaverage(target1ICAmanip);
    nt1ICAmanip = movingaverage(xnt1ICAmanip);
    if strcmp(nt2,'none')
        nt2ICAmanip = [];
    else
        nt2ICAmanip = movingaverage(xnt2ICAmanip);
        nt2ICAmanip = nt2ICAmanip(:,6:20,:);
    end
    targetICAmanip = targetICAmanip(:,6:20,:);
    nt1ICAmanip = nt1ICAmanip(:,6:20,:);
```

```
    % computes PCA extraction on epochs
    [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

    targetPCA = movingaverage(target1PCA);
    nt1PCA = movingaverage(xnt1PCA);
    if strcmp(nt2,'none')
        nt2PCA = [];
    else
        nt2PCA = movingaverage(xnt2PCA);
        nt2PCA = nt2PCA(:,6:20,:);
    end
    targetPCA = targetPCA(:,6:20,:);
    nt1PCA = nt1PCA(:,6:20,:);

    save file1 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA -V6

else

    NUM_FAC = input('How many factors would you like to retain? ');

    compute_laplac = input('Would you like to compute a surface laplacian (Y or N)? ', 's');

    file1 = input('What is the first files name? ', 's');
    targetfile1 = input('What is the target event for the first file? ', 's');
    ques = input('How many non-target events are there (0,1 or 2)? ');
    if ques == 1
        nt1file1 = input('What is the non-target event? ', 's');
        nt2file1 = 'none';
    elseif ques == 2
        nt1file1 = input('What is the first non-target event? ', 's');
        nt2file1 = input('What is the second non-target event? ', 's');
    elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
```

```
        error('Incorrect entry!');
    else
        nt1file1 = 'none';
        nt2file1 = 'none';
    end

    trials1 = [];
    ques = input('Which trials would you like to remove (0 = none)? ');
    if ques == 0;
        trials1 = [];
    else
        trials1 = cat(2,trials1,ques);
        ques = 1;
        while ques ~= 0
            ques = input('Which other trials would you like to remove (0 to end)? ');
            trials1 = cat(2,trials1,ques);
        end
    end

    file2 = input('What is the second files name? ', 's');
    targetfile2 = input('What is the target event for the second file? ', 's');
    ques = input('How many non-target events are there (0,1 or 2)? ');
    if ques == 1
        nt1file2 = input('What is the non-target event? ', 's');
        nt2file2 = 'none';
    elseif ques == 2
        nt1file2 = input('What is the first non-target event? ', 's');
        nt2file2 = input('What is the second non-target event? ', 's');
    elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
        error('Incorrect entry!');
    else
        nt1file2 = 'none';
        nt2file2 = 'none';
    end
```

```
trials2 = [];
ques = input('Which trials would you like to remove (0 = none)? ');
if ques == 0;
    trials2 = [];
else
    trials2 = cat(2,trials2,ques);
    ques = 1;
    while ques ~= 0
        ques = input('Which other trials would you like to remove (0 to end)? ');
        trials2 = cat(2,trials2,ques);
    end
end

file3 = input('What is the third files name (enter "none" to stop)? ', 's');
if strcmp(file3,'none')
    file4 = 'none';
    file5 = 'none';
    file6 = 'none';
else
    targetfile3 = input('What is the target event for the third file? ', 's');
    ques = input('How many non-target events are there (0,1 or 2)? ');
    if ques == 1
        nt1file3 = input('What is the non-target event? ', 's');
        nt2file3 = 'none';
    elseif ques == 2
        nt1file3 = input('What is the first non-target event? ', 's');
        nt2file3 = input('What is the second non-target event? ', 's');
    elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
        error('Incorrect entry!');
    else
        nt1file3 = 'none';
        nt2file3 = 'none';
    end
```

```
        trials3 = [];
        ques = input('Which trials would you like to remove (0 = none)? ');
        if ques == 0;
            trials3 = [];
        else
            trials3 = cat(2,trials3,ques);
            ques = 1;
            while ques ~= 0
                ques = input('Which other trials would you like to remove (0 to end)? ');
                trials3 = cat(2,trials3,ques);
            end
        end

        file4 = input('What is the fourth files name (enter "none" to stop)? ', 's');
    end

    if strcmp(file4,'none')
        file5 = 'none';
        file6 = 'none';
    else
        targetfile4 = input('What is the target event for the fourth file? ', 's');
        ques = input('How many non-target events are there (0,1 or 2)? ');
        if ques == 1
            nt1file4 = input('What is the non-target event? ', 's');
            nt2file4 = 'none';
        elseif ques == 2
            nt1file4 = input('What is the first non-target event? ', 's');
            nt2file4 = input('What is the second non-target event? ', 's');
        elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
            error('Incorrect entry!');
        else
            nt1file4 = 'none';
            nt2file4 = 'none';
```

```
        end

        trials4 = [];
        ques = input('Which trials would you like to remove (0 = none)? ');
        if ques == 0;
            trials4 = [];
        else
            trials4 = cat(2,trials4,ques);
            ques = 1;
            while ques ~= 0
                ques = input('Which other trials would you like to remove (0 to end)? ');
                trials4 = cat(2,trials4,ques);
            end
        end

        file5 = input('What is the fifth files name (enter "none" to stop)? ', 's');
    end

    if strcmp(file5,'none')
        file6 = 'none';
    else
        targetfile5 = input('What is the target event for the fifth file? ', 's');
        ques = input('How many non-target events are there (0,1 or 2)? ');
        if ques == 1
            nt1file5 = input('What is the non-target event? ', 's');
            nt2file5 = 'none';
        elseif ques == 2
            nt1file5 = input('What is the first non-target event? ', 's');
            nt2file5 = input('What is the second non-target event? ', 's');
        elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
            error('Incorrect entry!');
        else
            nt1file5 = 'none';
            nt2file5 = 'none';
```

```
    end

    trials5 = [];
    ques = input('Which trials would you like to remove (0 = none)? ');
    if ques == 0;
        trials5 = [];
    else
        trials5 = cat(2,trials5,ques);
        ques = 1;
        while ques ~= 0
            ques = input('Which other trials would you like to remove (0 to end)? ');
            trials5 = cat(2,trials5,ques);
        end
    end

    file6 = input('What is the sixth files name (enter "none" to stop)? ', 's');
end

if strcmp(file6,'none')
else
    targetfile6 = input('What is the target event for the sixth file? ', 's');
    ques = input('How many non-target events are there (0,1 or 2)? ');
    if ques == 1
        nt1file6 = input('What is the non-target event? ', 's');
        nt2file6 = 'none';
    elseif ques == 2
        nt1file6 = input('What is the first non-target event? ', 's');
        nt2file6 = input('What is the second non-target event? ', 's');
    elseif (ques ~= 0) && (ques ~= 1) && (ques ~= 2)
        error('Incorrect entry!');
    else
        nt1file6 = 'none';
        nt2file6 = 'none';
    end
```

```
        trials6 = [];
        ques = input('Which trials would you like to remove (0 = none)? ');
        if ques == 0;
            trials6 = [];
        else
            trials6 = cat(2,trials6,ques);
            ques = 1;
            while ques ~= 0
                ques = input('Which other trials would you like to remove (0 to end)? ');
                trials6 = cat(2,trials6,ques);
            end
        end

    end

    channel = input('Choose a channel to view (1 -> 129): ');

    % file1
    % perform pre-processing
    filtereddata = extractallERPsfromrawdata(file1,targetfile1,nt1file1,nt2file1,compute_laplac,trials1);

    % extract separate epochs
    [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-ICA',targetfile1,nt1file1,nt2file1,NUM_FAC);

    targetn = movingaverage(target1n);
    nt1n = movingaverage(xnt1n);
    if strcmp(nt2file1,'none')
        nt2n = [];
    else
        nt2n = movingaverage(xnt2n);
        nt2n = nt2n(:,6:20,:);
    end
```

```
    targetn = targetn(:,6:20,:);
    nt1n = nt1n(:,6:20,:);

    % performs extended ICA extraction with weighted Varimax PCA data reduction
    [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile1,nt1file1,nt2file1,NUM_FAC);

    targetICA = movingaverage(target1ICA);
    nt1ICA = movingaverage(xnt1ICA);
    if strcmp(nt2file1,'none')
        nt2ICA = [];
    else
        nt2ICA = movingaverage(xnt2ICA);
        nt2ICA = nt2ICA(:,6:20,:);
    end
    targetICA = targetICA(:,6:20,:);
    nt1ICA = nt1ICA(:,6:20,:);

    % spatio-temporally manipulates independent components
    [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

    targetICAmanip = movingaverage(target1ICAmanip);
    nt1ICAmanip = movingaverage(xnt1ICAmanip);
    if strcmp(nt2file1,'none')
        nt2ICAmanip = [];
    else
        nt2ICAmanip = movingaverage(xnt2ICAmanip);
        nt2ICAmanip = nt2ICAmanip(:,6:20,:);
    end
    targetICAmanip = targetICAmanip(:,6:20,:);
    nt1ICAmanip = nt1ICAmanip(:,6:20,:);

    % computes PCA extraction on epochs
```

```
    [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

    targetPCA = movingaverage(target1PCA);
    nt1PCA = movingaverage(xnt1PCA);
    if strcmp(nt2file1,'none')
        nt2PCA = [];
    else
        nt2PCA = movingaverage(xnt2PCA);
        nt2PCA = nt2PCA(:,6:20,:);
    end
    targetPCA = targetPCA(:,6:20,:);
    nt1PCA = nt1PCA(:,6:20,:);

    save file1 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA -V6

    clear targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA nt2PCA

    % file2
    % perform pre-processing
    filtereddata = extractallERPsfromrawdata(file2,targetfile2,nt1file2,nt2file2,compute_laplac,trials2);

    % extract separate epochs
    [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-ICA',targetfile2,nt1file2,nt2file2,NUM_FAC);

    targetn = movingaverage(target1n);
    nt1n = movingaverage(xnt1n);
    if strcmp(nt2file2,'none')
        nt2n = [];
    else
        nt2n = movingaverage(xnt2n);
        nt2n = nt2n(:,6:20,:);
    end
```

```
    targetn = targetn(:,6:20,:);
    nt1n = nt1n(:,6:20,:);

    % performs extended ICA extraction with weighted Varimax PCA data reduction
    [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile2,nt1file2,nt2file2,NUM_FAC);

    targetICA = movingaverage(target1ICA);
    nt1ICA = movingaverage(xnt1ICA);
    if strcmp(nt2file2,'none')
        nt2ICA = [];
    else
        nt2ICA = movingaverage(xnt2ICA);
        nt2ICA = nt2ICA(:,6:20,:);
    end
    targetICA = targetICA(:,6:20,:);
    nt1ICA = nt1ICA(:,6:20,:);

    % spatio-temporally manipulates independent components
    [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

    targetICAmanip = movingaverage(target1ICAmanip);
    nt1ICAmanip = movingaverage(xnt1ICAmanip);
    if strcmp(nt2file2,'none')
        nt2ICAmanip = [];
    else
        nt2ICAmanip = movingaverage(xnt2ICAmanip);
        nt2ICAmanip = nt2ICAmanip(:,6:20,:);
    end
    targetICAmanip = targetICAmanip(:,6:20,:);
    nt1ICAmanip = nt1ICAmanip(:,6:20,:);

    % computes PCA extraction on epochs
```

```
    [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

    targetPCA = movingaverage(target1PCA);
    nt1PCA = movingaverage(xnt1PCA);
    if strcmp(nt2file2,'none')
        nt2PCA = [];
    else
        nt2PCA = movingaverage(xnt2PCA);
        nt2PCA = nt2PCA(:,6:20,:);
    end
    targetPCA = targetPCA(:,6:20,:);
    nt1PCA = nt1PCA(:,6:20,:);

    save file2 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA -V6

    clear targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA nt2PCA

    if strcmp(file3,'none')
    else
        % file3
        % perform pre-processing
        filtereddata = extractallERPsfromrawdata(file3,targetfile3,nt1file3,nt2file3,compute_laplac,trials3);

        % extract separate epochs
        [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-
ICA',targetfile3,nt1file3,nt2file3,NUM_FAC);

        targetn = movingaverage(target1n);
        nt1n = movingaverage(xnt1n);
        if strcmp(nt2file3,'none')
            nt2n = [];
        else
```

```
            nt2n = movingaverage(xnt2n);
            nt2n = nt2n(:,6:20,:);
        end
        targetn = targetn(:,6:20,:);
        nt1n = nt1n(:,6:20,:);

        % performs extended ICA extraction with weighted Varimax PCA data reduction
        [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile3,nt1file3,nt2file3,NUM_FAC);

        targetICA = movingaverage(target1ICA);
        nt1ICA = movingaverage(xnt1ICA);
        if strcmp(nt2file3,'none')
            nt2ICA = [];
        else
            nt2ICA = movingaverage(xnt2ICA);
            nt2ICA = nt2ICA(:,6:20,:);
        end
        targetICA = targetICA(:,6:20,:);
        nt1ICA = nt1ICA(:,6:20,:);

        % temporo-spatially manipulates independent components
        [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

        targetICAmanip = movingaverage(target1ICAmanip);
        nt1ICAmanip = movingaverage(xnt1ICAmanip);
        if strcmp(nt2file3,'none')
            nt2ICAmanip = [];
        else
            nt2ICAmanip = movingaverage(xnt2ICAmanip);
            nt2ICAmanip = nt2ICAmanip(:,6:20,:);
        end
        targetICAmanip = targetICAmanip(:,6:20,:);
        nt1ICAmanip = nt1ICAmanip(:,6:20,:);
```

```
        % computes PCA extraction on epochs
        [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

        targetPCA = movingaverage(target1PCA);
        nt1PCA = movingaverage(xnt1PCA);
        if strcmp(nt2file3,'none')
            nt2PCA = [];
        else
            nt2PCA = movingaverage(xnt2PCA);
            nt2PCA = nt2PCA(:,6:20,:);
        end
        targetPCA = targetPCA(:,6:20,:);
        nt1PCA = nt1PCA(:,6:20,:);

        save file3 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA
nt1PCA nt2PCA -V6

        clear targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA
    end

    if strcmp(file4,'none')
    else
        % file4
        % perform pre-processing
        filtereddata = extractallERPsfromrawdata(file4,targetfile4,nt1file4,nt2file4,compute_laplac,trials4);

        % extract separate epochs
        [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-
ICA',targetfile4,nt1file4,nt2file4,NUM_FAC);

        targetn = movingaverage(target1n);
```

```
        nt1n = movingaverage(xnt1n);
        if strcmp(nt2file4,'none')
            nt2n = [];
        else
            nt2n = movingaverage(xnt2n);
            nt2n = nt2n(:,6:20,:);
        end
        targetn = targetn(:,6:20,:);
        nt1n = nt1n(:,6:20,:);

        % performs extended ICA extraction with weighted Varimax PCA data reduction
        [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile4,nt1file4,nt2file4,NUM_FAC);

        targetICA = movingaverage(target1ICA);
        nt1ICA = movingaverage(xnt1ICA);
        if strcmp(nt2file4,'none')
            nt2ICA = [];
        else
            nt2ICA = movingaverage(xnt2ICA);
            nt2ICA = nt2ICA(:,6:20,:);
        end
        targetICA = targetICA(:,6:20,:);
        nt1ICA = nt1ICA(:,6:20,:);

        % temporo-spatially manipulates independent components
        [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

        targetICAmanip = movingaverage(target1ICAmanip);
        nt1ICAmanip = movingaverage(xnt1ICAmanip);
        if strcmp(nt2file4,'none')
            nt2ICAmanip = [];
        else
            nt2ICAmanip = movingaverage(xnt2ICAmanip);
```

```
            nt2ICAmanip = nt2ICAmanip(:,6:20,:);
        end
        targetICAmanip = targetICAmanip(:,6:20,:);
        nt1ICAmanip = nt1ICAmanip(:,6:20,:);

        % computes PCA extraction on epochs
        [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

        targetPCA = movingaverage(target1PCA);
        nt1PCA = movingaverage(xnt1PCA);
        if strcmp(nt2file4,'none')
            nt2PCA = [];
        else
            nt2PCA = movingaverage(xnt2PCA);
            nt2PCA = nt2PCA(:,6:20,:);
        end
        targetPCA = targetPCA(:,6:20,:);
        nt1PCA = nt1PCA(:,6:20,:);

        save file4 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA
nt1PCA nt2PCA -V6

        clear targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA
    end

    if strcmp(file5,'none')
    else
        % file5
        % perform pre-processing
        filtereddata = extractallERPsfromrawdata(file5,targetfile5,nt1file5,nt2file5,compute_laplac,trials5);

        % extract separate epochs
```

```
        [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-
ICA',targetfile5,nt1file5,nt2file5,NUM_FAC);

        targetn = movingaverage(target1n);
        nt1n = movingaverage(xnt1n);
        if strcmp(nt2file5,'none')
            nt2n = [];
        else
            nt2n = movingaverage(xnt2n);
            nt2n = nt2n(:,6:20,:);
        end
        targetn = targetn(:,6:20,:);
        nt1n = nt1n(:,6:20,:);

        % performs extended ICA extraction with weighted Varimax PCA data reduction
        [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile5,nt1file5,nt2file5,NUM_FAC);

        targetICA = movingaverage(target1ICA);
        nt1ICA = movingaverage(xnt1ICA);
        if strcmp(nt2file5,'none')
            nt2ICA = [];
        else
            nt2ICA = movingaverage(xnt2ICA);
            nt2ICA = nt2ICA(:,6:20,:);
        end
        targetICA = targetICA(:,6:20,:);
        nt1ICA = nt1ICA(:,6:20,:);

        % temporo-spatially manipulates independent components
        [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

        targetICAmanip = movingaverage(target1ICAmanip);
```

```
        nt1ICAmanip = movingaverage(xnt1ICAmanip);
        if strcmp(nt2file5,'none')
            nt2ICAmanip = [];
        else
            nt2ICAmanip = movingaverage(xnt2ICAmanip);
            nt2ICAmanip = nt2ICAmanip(:,6:20,:);
        end
        targetICAmanip = targetICAmanip(:,6:20,:);
        nt1ICAmanip = nt1ICAmanip(:,6:20,:);

        % computes PCA extraction on epochs
        [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

        targetPCA = movingaverage(target1PCA);
        nt1PCA = movingaverage(xnt1PCA);
        if strcmp(nt2file5,'none')
            nt2PCA = [];
        else
            nt2PCA = movingaverage(xnt2PCA);
            nt2PCA = nt2PCA(:,6:20,:);
        end
        targetPCA = targetPCA(:,6:20,:);
        nt1PCA = nt1PCA(:,6:20,:);

        save file5 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA
nt1PCA nt2PCA -V6

        clear targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA nt1PCA
nt2PCA
    end

    if strcmp(file6,'none')
    else
```

```
        % file6
        % perform pre-processing
        filtereddata = extractallERPsfromrawdata(file6,targetfile6,nt1file6,nt2file6,compute_laplac,trials6);

        % extract separate epochs
        [target1n,xnt1n,xnt2n] = extractseparateevents(filtereddata,'non-
ICA',targetfile6,nt1file6,nt2file6,NUM_FAC);

        targetn = movingaverage(target1n);
        nt1n = movingaverage(xnt1n);
        if strcmp(nt2file6,'none')
            nt2n = [];
        else
            nt2n = movingaverage(xnt2n);
            nt2n = nt2n(:,6:20,:);
        end
        targetn = targetn(:,6:20,:);
        nt1n = nt1n(:,6:20,:);

        % performs extended ICA extraction with weighted Varimax PCA data reduction
        [target1ICA,xnt1ICA,xnt2ICA,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,'ICA',targetfile6,nt1file6,nt2file6,NUM_FAC);

        targetICA = movingaverage(target1ICA);
        nt1ICA = movingaverage(xnt1ICA);
        if strcmp(nt2file6,'none')
            nt2ICA = [];
        else
            nt2ICA = movingaverage(xnt2ICA);
            nt2ICA = nt2ICA(:,6:20,:);
        end
        targetICA = targetICA(:,6:20,:);
        nt1ICA = nt1ICA(:,6:20,:);
```

```
        % temporo-spatially manipulates independent components
        [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3);

        targetICAmanip = movingaverage(target1ICAmanip);
        nt1ICAmanip = movingaverage(xnt1ICAmanip);
        if strcmp(nt2file6,'none')
            nt2ICAmanip = [];
        else
            nt2ICAmanip = movingaverage(xnt2ICAmanip);
            nt2ICAmanip = nt2ICAmanip(:,6:20,:);
        end
        targetICAmanip = targetICAmanip(:,6:20,:);
        nt1ICAmanip = nt1ICAmanip(:,6:20,:);

        % computes PCA extraction on epochs
        [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n);

        targetPCA = movingaverage(target1PCA);
        nt1PCA = movingaverage(xnt1PCA);
        if strcmp(nt2file6,'none')
            nt2PCA = [];
        else
            nt2PCA = movingaverage(xnt2PCA);
            nt2PCA = nt2PCA(:,6:20,:);
        end
        targetPCA = targetPCA(:,6:20,:);
        nt1PCA = nt1PCA(:,6:20,:);

        save file6 targetn nt1n nt2n targetICA nt1ICA nt2ICA targetICAmanip nt1ICAmanip nt2ICAmanip targetPCA
nt1PCA nt2PCA -V6
    end
end
```

L.2 Extract and pre-process all ERPs from the raw EEG data

```
function filtereddata = extractallERPsfromrawdata(file,target,nt1,nt2,compute_laplac,trials)
% extractallERPsfromrawdata - filtereddata = extractallERPsfromrawdata(file,target,nt1,nt2) -
% extract all event epochs from raw data
%Inputs
%  file     : filename ('filename.raw')
%  target   : the target event
%  nt1      : non-target 1
%  nt2      : non-target 2
%
%Outputs
%  filtereddata     : processed event epochs (channels,timepoints,epochs)
%
% extractallERPsfromrawdata extracts all event epochs from raw EEG data
% recordings. The following occurs:
% - it is 0.1 - 8 Hz band-pass filtered
% - referenced to the mastoid electrode (101)
% - epochs are extracted (from the time of the event to 650ms after)
% - unwanted trials/epochs are removed
% - and it is baseline corrected

% process only the target data
if strcmp(nt1,'none')
    EEG = pop_readegi(file, []);
    EEG = eeg_checkset( EEG );
    EEG=pop_chanedit(EEG,  'load',{ 'C:\My Data\GSN129b.sfp', 'filetype', 'autodetect'}); % load channel locations
file
    EEG = eeg_checkset( EEG );
    % compute surface laplacian
    if strcmp(compute_laplac,'Y')
        EEG = pop_reref( EEG, [], 'refstate',129, 'keepref', 'on', 'method', 'withref');
        EEG = eeg_checkset( EEG );
```

```
        newEEG = zeros(129,302,180);
        for i = 1:size(EEG.data,3)
            [laplac] = del2map(squeeze(EEG.data(:,:,i)), 'GSN129b.sfp');
            newEEG(:,:,i) = laplac;
        end
        EEG.data = newEEG;
    end
    % 0.1 to 8 Hz band-pass filter the data
    EEG = pop_eegfilt( EEG, 0, 8, [], [0]); % 8 Hz lowpass filtered
    EEG = eeg_checkset( EEG );
    EEG = pop_eegfilt( EEG, 0.1, 0, [], [0]); % 0.1 Hz highpass filtered
    EEG = eeg_checkset( EEG );
    % rereference to the right mastoid electrode
    EEG = pop_reref( EEG, 101, 'refstate',129, 'keepref', 'on', 'method', 'withref');
    EEG = eeg_checkset( EEG );
    % remove bad trials manually
    if isempty(trials)
    else
    EEG = pop_select( EEG, 'notrial',[trials]); % remove other trials
    EEG = eeg_checkset( EEG );
    end
    % remove baseline
    EEG = pop_rmbase( EEG, [0  505]);
    EEG = eeg_checkset( EEG );
    % extract epochs from 0 to 650ms post stimulus
    EEG = pop_epoch( EEG, {  target  }, [0          0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    filtereddata = EEG;
% process the target and a non-target data
elseif strcmp(nt2,'none')
    EEG = pop_readegi(file, []);
    EEG = eeg_checkset( EEG );
    EEG=pop_chanedit(EEG,  'load',{ 'C:\My Data\GSN129b.sfp', 'filetype', 'autodetect'});
    EEG = eeg_checkset( EEG );
```

```
    if strcmp(compute_laplac,'Y')
        EEG = pop_reref( EEG, [], 'refstate',129, 'keepref', 'on', 'method', 'withref');
        EEG = eeg_checkset( EEG );
        newEEG = zeros(129,302,180);
        for i = 1:size(EEG.data,3)
            [laplac] = del2map(squeeze(EEG.data(:,:,i)), 'GSN129b.sfp');
            newEEG(:,:,i) = laplac;
        end
        EEG.data = newEEG;
    end
    EEG = pop_eegfilt( EEG, 0, 8, [], [0]);
    EEG = eeg_checkset( EEG );
    EEG = pop_eegfilt( EEG, 0.1, 0, [], [0]);
    EEG = eeg_checkset( EEG );
    EEG = pop_reref( EEG, 101, 'refstate',129, 'keepref', 'on', 'method', 'withref');
    EEG = eeg_checkset( EEG );
    if isempty(trials)
    else
    EEG = pop_select( EEG, 'notrial',[trials]);
    EEG = eeg_checkset( EEG );
    end
    EEG = pop_rmbase( EEG, [0  505]);
    EEG = eeg_checkset( EEG );
    EEG = pop_epoch( EEG, {  target nt1  }, [0          0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    filtereddata = EEG;
% process the target and two non-targets datasets
else
    EEG = pop_readegi(file, []);
    EEG = eeg_checkset( EEG );
    EEG=pop_chanedit(EEG,  'load',{ 'C:\My Data\GSN129b.sfp', 'filetype', 'autodetect'});
    EEG = eeg_checkset( EEG );
    if strcmp(compute_laplac,'Y')
        EEG = pop_reref( EEG, [], 'refstate',129, 'keepref', 'on', 'method', 'withref');
```

```
        EEG = eeg_checkset( EEG );
        newEEG = zeros(129,302,180);
        for i = 1:size(EEG.data,3)
            [laplac] = del2map(squeeze(EEG.data(:,:,i)), 'GSN129b.sfp');
            newEEG(:,:,i) = laplac;
        end
        EEG.data = newEEG;
    end
    EEG = pop_eegfilt( EEG, 0, 8, [], [0]);
    EEG = eeg_checkset( EEG );
    EEG = pop_eegfilt( EEG, 0.1, 0, [], [0]);
    EEG = eeg_checkset( EEG );
    EEG = pop_reref( EEG, 101, 'refstate',129, 'keepref', 'on', 'method', 'withref');
    EEG = eeg_checkset( EEG );
    if isempty(trials)
    else
    EEG = pop_select( EEG, 'notrial',[trials]);
    EEG = eeg_checkset( EEG );
    end
    EEG = pop_rmbase( EEG, [0    505]);
    EEG = eeg_checkset( EEG );
    EEG = pop_epoch( EEG, {  target nt1 nt2  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo',
'yes');
    EEG = eeg_checkset( EEG );
    filtereddata = EEG;
end
```

L.3 Extract separate events from concatenated data

```
function [target1,xnt1,xnt2,act1,act2,act3,Unmixing_Matrix] =
extractseparateevents(filtereddata,type,target,nt1,nt2,NUM_FAC)
% extractseparateevents - [target1,xnt1,xnt2,act1,act2,act3,Unmixing_Matrix] =
% extractseparateevents(filtereddata,type,target,nt1,nt2,NUM_FAC) -
```

```
% extract separate events from concatenated data
%Inputs
%  filtereddata  : concatenated data (channels,timepoints,trials)
%  type          : 'ICA' or no ICA performed
%  target        : target event
%  nt1           : non-target 1 event
%  nt2           : non-target 2 event
%  NUM_FAC       : number of components to retain
%
%Outputs
%  target1         : target matrix
%  xnt1            : non-target 1 matrix
%  xnt2            : non-target 2 matrix
%  act1,act2,act3  : ICA activations for the three events
%  Unmixing_Matrix : the ICA demixing matrix
%
% extractseparateevents extracts all event epochs from EEG data. The
% following occurs:
% - ICA is possibly performed according to the input
% - separate events are extracted

EEG = filtereddata;

if strcmp(nt1,'none')
    % perform extended ICA with PCA reduction using embedded EEGLAB
    % functionality
    if strcmp(type,'ICA')
        EEG = pop_runica(EEG,  'icatype', 'runica', 'dataset',1, 'options',{ 'pca',NUM_FAC, 'extended',1});
        Unmixing_Matrix = EEG.icaweights;
    end
    % extract event
    EEG = pop_epoch( EEG, {  target  }, [0           650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    target1 = EEG.data;
```

```
    if strcmp(type,'ICA')
        act1 = EEG.icaact;
    else
        act1 = [];
    end
    xnt1 = [];
    act2 = [];
    xnt2 = [];
    act3 = [];
elseif strcmp(nt2,'none')
    if strcmp(type,'ICA')
        EEG = pop_runica(EEG,  'icatype', 'runica', 'dataset',1, 'options',{ 'pca',NUM_FAC, 'extended',1});
        Unmixing_Matrix = EEG.icaweights;
    else
        Unmixing_Matrix = [];
    end
    recall = EEG;
    EEG = pop_epoch( EEG, {  target  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    target1 = EEG.data;
    if strcmp(type,'ICA')
        act1 = EEG.icaact;
    else
        act1 = [];
    end
    EEG = recall;
    EEG = pop_epoch( EEG, {  nt1  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    xnt1 = EEG.data;
    if strcmp(type,'ICA')
        act2 = EEG.icaact;
    else
        act2 = [];
    end
```

```
    xnt2 = [];
    act3 = [];
else
    if strcmp(type,'ICA')
        EEG = pop_runica(EEG,  'icatype', 'runica', 'dataset',1, 'options',{ 'pca',NUM_FAC, 'extended',1});
        Unmixing_Matrix = EEG.icaweights;
    else
        Unmixing_Matrix = [];
    end
    recall = EEG;
    EEG = pop_epoch( EEG, {  target  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    target1 = EEG.data;
    if strcmp(type,'ICA')
        act1 = EEG.icaact;
    else
        act1 = [];
    end
    EEG = recall;
    EEG = pop_epoch( EEG, {  nt1  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    xnt1 = EEG.data;
    if strcmp(type,'ICA')
        act2 = EEG.icaact;
    else
        act2 = [];
    end
    EEG = recall;
    EEG = pop_epoch( EEG, {  nt2  }, [0           0.650], 'newname', 'EGI file epochs', 'epochinfo', 'yes');
    EEG = eeg_checkset( EEG );
    xnt2 = EEG.data;
    if strcmp(type,'ICA')
        act3 = EEG.icaact;
    else
```

```
        act3 = [];
    end
end
```

L.4 Calculate the moving average under the curve for successive periods of each channel

```
function output = movingaverage(data)
% movingaverage - output = movingaverage(data) - calculates the
% average within a window under the curve for successive periods and
% outputs the answer for each channel
%Inputs
%  data     : epoched data for all channels(channels,timepoints,epochs)
%
%Outputs
%  output   : output of window averaging
%
% movingaverage calculates the mean under the curve for a succesive time
% periods for each channel and outputs the results in an array

final = [];
area = 0;
output = [];

for m = 1:size(data,1)
    channels = squeeze(data(m,:,:));
    results = zeros(size(channels,2),25); % initialise results matrix
    for i = 1:size(channels,2)
        for j = 0:5:120
            for k = 1:10
                area = area + channels(j+k,i);
            end
            final = cat(2,final,area/10);
            area = 0;
```

```
        end
        results(i,:) = final(:); % input channel averaging data into results matrix
        final = [];
    end
    output(m,:,:) = results';
end
```

L.5 Temporal and spatial manipulation of data

```
function [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] = tempspatmanip(Unmixing_Matrix,act1,act2,act3)
% tempspatmanip - [target1ICAmanip,xnt1ICAmanip,xnt2ICAmanip] =
% tempspatmanip(Unmixing_Matrix,act1,act2,act3) - perform temporo-spatial
% manipulation of data for P300 enhancement
%
%Inputs
%  Unmixing_Matrix     : ICA demixing matrix
%  act1,act2,act3      : ICA activations or independent components
%
%Outputs
%  target1ICAmanip, xnt1ICAmanip, xnt2ICAmanip are the temporo-spatially
%  manipulated matrices

disp('Performing temporo-spatial manipulation of data...');

% timeband between which the P300 is detected
startP300 = 50;
finishP300 = 80;
u = [];
unt1 = [];
unt2 = [];
for i = 1:size(act1,3)
    newdata = tempmanip(squeeze(act1(:,:,i)),startP300,finishP300);
    u = cat(3,u,newdata);
```

```
end
for i = 1:size(act2,3)
    newdatant1 = tempmanip(squeeze(act2(:,:,i)),startP300,finishP300);
    unt1 = cat(3,unt1,newdatant1);
end
if isempty(act3)
else
    for i = 1:size(act3,3)
        newdatant2 = tempmanip(squeeze(act3(:,:,i)),startP300,finishP300);
        unt2 = cat(3,unt2,newdatant2);
    end
end

% spatial manipulation according to 49 predetermined electrodes covering
% P300 spatial location on the scalp
intensity = 49;
targetICs = [];
nt1ICs = [];
nt2ICs = [];
for i = 1:size(u,3)
    newdata = spatmanip(u(:,:,i),Unmixing_Matrix,intensity);
    targetICs = cat(3,targetICs,newdata);
end
for i = 1:size(unt1,3)
    newdatant1 = spatmanip(unt1(:,:,i),Unmixing_Matrix,intensity);
    nt1ICs = cat(3,nt1ICs,newdatant1);
end
if isempty(act3)
else
    for i = 1:size(unt2,3)
        newdatant2 = spatmanip(unt2(:,:,i),Unmixing_Matrix,intensity);
        nt2ICs = cat(3,nt2ICs,newdatant2);
    end
end
```

```
target1ICAmanip = [];
xnt1ICAmanip = [];
xnt2ICAmanip = [];

% inverse transform of temporo-spatially manipulated data
for i = 1:size(targetICs,3)
    newdata = pinv(Unmixing_Matrix)*targetICs(:,:,i);
    target1ICAmanip = cat(3,target1ICAmanip,newdata);
end
for i = 1:size(nt1ICs,3)
    newdatant1 = pinv(Unmixing_Matrix)*nt1ICs(:,:,i);
    xnt1ICAmanip = cat(3,xnt1ICAmanip,newdatant1);
end
if isempty(act3)
else
    for i = 1:size(nt2ICs,3)
        newdatant2 = pinv(Unmixing_Matrix)*nt2ICs(:,:,i);
        xnt2ICAmanip = cat(3,xnt2ICAmanip,newdatant2);
    end
end
```

L.6 Temporal manipulation

```
function newdata = tempmanip(data,startP300,finishP300)
% tempmanip - newdata = tempmanip(data) - do temporal manipulation on ICs
% and calculate the new data matrix
%Inputs
%  data        : data matrix (ICs,timepoints)
%  startP300   : start point for P300 latency range
%  finishP300  : end point for P300 latency range
%
```

```
%Outputs
%  newdata  : temporally manipulated data
%
% tempmanip manipulates the data matrix (generated from the trained
% demixing matrix) so as to keep the ICs with relatively larger amplitudes
% in the latency range of the ERP in question and to zero all other ICs.

timepoints = size(data,2); % number of time points in the data
numIC = size(data,1); % number of ICs in the data

rawdata = zeros(numIC,timepoints);
for k = 1:size(data,1)
        maxamp1 = 0;
        maxamp2 = 0;
        current1 = data(k,startP300);
        current2 = data(k,startP300);
        for j = startP300:finishP300
            if data(k,j) > 0 && data(k,j) > current1
                maxamp1 = j;
                current1 = data(k,j);
            end
            if data(k,j) < 0 && data(k,j) < current2
                maxamp2 = j;
                current2 = data(k,j);
            end
        end
        % include data where peak is in P300 latency range
        if maxamp1 > startP300 && maxamp1 < finishP300
            rawdata(k,:) = data(k,:);
        elseif maxamp2 > startP300 && maxamp2 < finishP300
            rawdata(k,:) = data(k,:);
        end
end
```

```
newdata = rawdata;
```

L.7 Spatial manipulation

```
function newdata = spatmanip(datatest,weights,threshold)
% spatmanip - newdata = spatmanip(data) - do spatial manipulation on ICs
% and calculate the new data matrix
%Inputs
%  data     : data matrix (channels,time points)
%  weights  : unmixing matrix
%  threshold: determines the number of channel influences from the intensity matrix
%
%Outputs
%  newdata  : spatially manipulated data
%
% spatmanip manipulates the data matrix (generated from the trained
% demixing matrix) so as to retain important information from specified
% electrode sites according to an intensity order matrix.

testdata = datatest;

w = 0;
for y = 1:size(datatest,1)
    if max(datatest(y,:) ~= 0) ~= 0
        w = w + 1;
    end
end

if w > 1.01

inverse = pinv(weights); % calculate pseudoinverse of unmixing matrix
numchan = size(inverse,1); % number of channels
numIC = size(inverse,2); % number of ICs
```

```
M = inverse;

sortinverse = sort(inverse,1,'descend'); % sort the colums of the pseudoinverse matrix in order of size

% compute intensity order matrix -  a matrix containing ICs with the
% intensity order of channels contributing to those ICs (1 = most intense;
% 129 = least intense)
for j = 1:numIC
    for i = 1:numchan
        test = sortinverse(i,j);
        for k = 1:numchan
            if M(k,j) == test
                M(k,j) = i;
            else
                M(k,j) = M(k,j);
            end
        end
    end
end

% predetermined channel set for P300 detection
Q = [11 30 21 12 5 119 112 13 6 113 42 37 31 7 107 106 105 104 48 43 38 32 129 81 88 94 99 51 52 53 54 55 80 87 93
98 58 59 60 61 62 79 86 92 97 66 72 77 85];

for j = 1:numIC
    t = 0;
    for i = 1:numchan
        for k = 1:size(Q,2)
            if Q(1,k) == i
                if M(i,j) <= threshold
                    t = 1;
                end
```

```
            end
        end
    end
    if t == 0
        datatest(j,:) = 0;
    end
end

while max(max(datatest)) == 0
    datatest = testdata;
    threshold = threshold + 1;
    for j = 1:numIC
    t = 0;
    for i = 1:numchan
        for k = 1:size(Q,2)
            if Q(1,k) == i
                if M(i,j) <= threshold
                    t = 1;
                end
            end
        end
    end
    if t == 0
        datatest(j,:) = 0;
    end
    end
end

newdata = datatest;
else
    newdata = datatest;
end
```

L.8 Perform PCA

```
function [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n)
% computePCA - [target1PCA,xnt1PCA,xnt2PCA]  = computePCA(NUM_FAC,target1n,xnt1n,xnt2n)
% - perform PCA transforamtion on data
%
%Inputs
%  NUM_FAC    : number of components to retain
%  target1n   : target matrix
%  xnt1n      : non-target 1 matrix (channels,timepoints,epochs)
%  xnt2n      : non-target 2 matrix (channels,timepoints,epochs)
%
%Outputs
%  target1PCA, xnt1PCA, xnt2PCA represent the PCA transformed data for each
%  event

disp('Performing PCA on data...');

target1PCA = zeros(size(target1n));

% calculate for each trial

% target
for i = 1:size(target1n,3)
current = squeeze(target1n(:,:,i))';
S = cov(current); % covariance matrix

[V,L] = eig(S); % calculate eigenvectors and eigenvalues

% reorder eigenvalue (largest to smallest - indicates factors with the most variance) and eigenvector matrix
L = flipud(fliplr(L));
V = fliplr(V);
```

```
NUM_VAR = size (S,1);  % number of variables
PCAmatrix = V(:,1:NUM_FAC);  % truncated eigenvector matrix
scree = diag(L);
L = L(1:NUM_FAC,1:NUM_FAC);  % truncated eigenvalue matrix

newdata = PCAmatrix'*current';

newtarget = PCAmatrix*newdata;

target1PCA(:,:,i) = newtarget;
end

xnt1PCA = zeros(size(xnt1n));

% non-target 1
for i = 1:size(xnt1n,3)

current = squeeze(xnt1n(:,:,i))';
S = cov(current); % covariance matrix

[V,L] = eig(S); % calculate eigenvectors and eigenvalues

% reorder eigenvalue (largest to smallest - indicates factors with the most variance) and eigenvector matrix
L = flipud(fliplr(L));
V = fliplr(V);

NUM_VAR = size (S,1);  % number of variables
PCAmatrix = V(:,1:NUM_FAC);  % truncated eigenvector matrix
scree = diag(L);
L = L(1:NUM_FAC,1:NUM_FAC);  % truncated eigenvalue matrix
```

```
newdata = PCAmatrix'*current';

newxnt1 = PCAmatrix*newdata;

nt1PCA(:,:,i) = newxnt1;

end

% non-target 2
if isempty(xnt2n)
    xnt2PCA = [];
else

xnt2PCA = zeros(size(xnt2n));

for i = 1:size(xnt2n,3)

current = squeeze(xnt2n(:,:,i))';
S = cov(current); % covariance matrix

[V,L] = eig(S); % calculate eigenvectors and eigenvalues

% reorder eigenvalue (largest to smallest - indicates factors with the most variance) and eigenvector matrix
L = flipud(fliplr(L));
V = fliplr(V);

NUM_VAR = size (S,1);  % number of variables
PCAmatrix = V(:,1:NUM_FAC);  % truncated eigenvector matrix
scree = diag(L);
L = L(1:NUM_FAC,1:NUM_FAC);  % truncated eigenvalue matrix

newdata = PCAmatrix'*current';
```

```
newxnt2 = PCAmatrix*newdata;

nt2PCA(:,:,i) = newxnt2;

end
end
```

L.9 Feature selection

```
function results =  featureselection(targetfeatures,nt1features,nt2features)
% featureselection - results =  featureselection(targetfeatures,nt1features,nt2features) -
% compute best feature selection set according to Thornton's separability
% index
%Inputs
%  targetfeatures   : target matrix (channels,features,trials)
%  nt1features      : non-target 1 matrix (channels,features,trials)
%  nt2features      : non_target 2 matrix (channels,features,trials)
%
%Output
%  results          : matrix consisting of best separability indices calculated
%                     for each channel according to varying feature sets,
%                     number of feature set for that index, maximum si and
%                     the associated channel, the feature set for that
%                     channel, and the feature set most commonly used

channelssi = [];
channelsbestset = [];

for i = 1:size(targetfeatures,1)

featureset = cat(1,(squeeze(targetfeatures(i,:,:)))',(squeeze(nt1features(i,:,:)))');
```

```
if isempty(nt2features)
else
    featureset = cat(1,featureset,(squeeze(nt2features(i,:,:)))');
end
classes = zeros(size(featureset,1),1);
classes(1:size(targetfeatures,3),:) = 1;
classes(size(targetfeatures,3)+1:size(featureset,1),:) = -1;

    featureset1 = featureset;
    featureset2 = featureset(:,1:10);
    featureset3 = featureset(:,1:15);
    featureset4 = featureset(:,1:20);
    featureset5 = featureset(:,16:25);
    featureset6 = featureset(:,11:25);
    featureset7 = featureset(:,6:25);
    featureset8 = featureset(:,11:20);
    featureset9 = featureset(:,6:20);
    featureset10 = featureset(:,6:15);
    si = 0;
    for k = 1:10
        % calculate separability index
        eval(['currentsi = sepindex(featureset' num2str(k) ',classes);']);
        if currentsi > si
            si = currentsi;
            bestset = k;
        end
    end
    channelssi = cat(2,channelssi,si);
    channelsbestset = cat(2,channelsbestset,bestset);
end

% determine best features of result
si_info = zeros(1,size(targetfeatures,1));
maximum_si = max(channelssi);
```

```
at_channel = find(channelssi == max(channelssi));
si_info(1,1) = maximum_si;
si_info(1,2:1+size(at_channel,2)) = at_channel;

channel_is_set = channelsbestset(at_channel);
maxset = 0;
fset = zeros(4,size(targetfeatures,1));
fset(1,1:size(channel_is_set,2)) = channel_is_set;
for i = 1:10
    current = histc(channelsbestset,i);
    if current > maxset;
        maxset = current;
        fset(2) = i;
    elseif current == maxset;
        if fset(3) == 0
            fset(3) = i;
        else
            fset(4) = i;
        end
    end
end

results = [channelssi; channelsbestset; si_info; fset];
```

Table L.1 An example of the determination of the best features using the GSI across an experimental set from subject 1. A = no signal processing, B = PCA, C = PCA and ICA, D = C including spatio-temporal manipulation, * = *many*. By process of elimination, feature set 9 provides the best discernible GSI across the most number of experiments and hence was chosen as the feature set.

	Experiment 1				Experiment 2				Experiment 3				Experiment 4				Experiment 5			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
BEST Feature Set	1	6	*	1	5	2/9	*	5	9	6	*	9	8	5/8	*	8	9	10	*	9
MOST USED Feature Set	1	6	2	1	2	3/5	2	2	2/8	2	2	2/8	3	10	2	3	3	8	2	3

L.10 Separability index

```
function s = sepindex(X,t)
% sepindex - s = sepindex(X,t) - calculate Thornton's separability index
%
%Inputs
%  X     : matrix of features (trials,features)
%  t     : classes for the trials (1 and -1)
%
%Output
%  s     : separability index

p = length(t);

d2 = dist2(X,X);
[S,I] = sort(d2);
t1 = t(I(1,:));
t2 = t(I(2,:));
```

```
s  = sum(t1 == t2)/p;

function n2 = dist2(x,c)
% dist2 - n2 = dist2(x,c) - computes nearest neighbour
%
%Inputs
%  x     : matrix of values
%  c     : matrix of neighbouring values
%
%Output
%  n2    : nearest neighbour matrix

[ndata,dimx] = size(x);
[ncentres,dimc] = size(c);
if dimx ~= dimc
    error('Data dimensions does not match dimensions of centres')
end

n2 = (ones(ncentres,1)*sum((x.^2)',1))' + ones(ndata,1)*sum((c.^2)',1) - 2.*(x*(c'));

% in the above 1 means add column-wise, if it were 2 add row-wise

if any(any(n2<0))
    n2(n2<0) = 0;
end
```

Appendix M Classification MATLAB Code

This section contains the MATLAB code used for classification of the processed data. The files include:

- Perform classification on processed data
- Linear SVM with C = 10

M.1 Perform classification on processed data

```
function performclassification()
% performclassification - performclassification() - perform full
% classification on datasets using a linear support vector machine of C
% parameters 0.1 and 10
%
% outputs are saved to file

ques1 = input('How many files for the 1st test? ');

for x = 5:ques1
    eval(['load firstfile' num2str(x)]);

    test10n = classifier10(targetn,nt1n,nt2n);

    test10ICA = classifier10(targetICA,nt1ICA,nt2ICA);

    test10ICAmanip = classifier10(targetICAmanip,nt1ICAmanip,nt2ICAmanip);

    test10PCA = classifier10(targetPCA,nt1PCA,nt2PCA);

    eval(['save file' num2str(x) 'classificationtest1 test10n test10ICA test10ICAmanip test10PCA']);

    clear test10n test10ICA test10ICAmanip test10PCA
end
```

M.2 Linear SVM with C = 10

```
function results = classifier10(targetdata,nt1data,nt2data)
% classifier10 - results = classifier10(targetdata,nt1data,nt2data) -
```

```
% classify input data using a linear support vector machine with C = 10
%
%Inputs
%  targetdata, nt1data, and nt2data are matrices of features
%
%Output
%  results   : matrix of correct classifications for separate channels,
%              specificity, sensitivity, positive predictive value,
%              negative predictive value, the maximum classification
%              channel and its value

clc
results = [];
channels = zeros(1,size(targetdata,1));
truen = zeros(1,size(targetdata,1));
truep = zeros(1,size(targetdata,1));
falsen = zeros(1,size(targetdata,1));
falsep = zeros(1,size(targetdata,1));
max_classification = zeros(1,size(targetdata,1));
max_channel = zeros(1,size(targetdata,1));
amounttotal = 0;

% perform 10 cross-validations on data
for r = 1:10

    channelssingle = [];
    true_n = [];
    true_p = [];
    false_n  = [];
    false_p = [];

    % select random events
    random_target = randperm(size(targetdata,3));
    random_nt1 = randperm(size(nt1data,3));
```

```
if isempty(nt2data)
else
    random_nt2 = randperm(size(nt2data,3));
end

% perform classification for each channel
for i = 1:size(targetdata,1)

    data = cat(1,(squeeze(targetdata(i,:,:)))',(squeeze(nt1data(i,:,:)))');
    if isempty(nt2data)
    else
        data = cat(1,data,(squeeze(nt2data(i,:,:)))');
    end
    classes = zeros(size(data,1),1);
    classes(1:size(targetdata,3),:) = 1;
    classes(size(targetdata,3)+1:size(data,1),:) = -1;

    targetdatatrain = squeeze(targetdata(i,:,:))';
    nt1datatrain = squeeze(nt1data(i,:,:))';
    if isempty(nt2data)
    else
        nt2datatrain = squeeze(nt2data(i,:,:))';
    end

    if isempty(nt2data)
        for k = 1:size(targetdata,3)-6
            data1(k,:) = targetdatatrain(random_target(k),:);
            classes1(k,1) = 1;
        end
        for k = 1:6
            test(k,:) = targetdatatrain(random_target(k + size(targetdata,3)-6),:);
            testclass(k,1) = 1;
        end
        for k = 1:size(targetdata,3)-6
```

```
                data1(k+size(targetdata,3)-6,:) = nt1datatrain(random_nt1(k),:);
                classes1(k+size(targetdata,3)-6,1) = -1;
            end
            for k = 1:6
                test(k+6,:) = nt1datatrain(random_nt1(k + size(targetdata,3)-6),:);
                testclass(k+6,1) = -1;
            end
        else
            for k = 1:size(targetdata,3)-10
                data1(k,:) = targetdatatrain(random_target(k),:);
                classes1(k,1) = 1;
            end
            for k = 1:10
                test(k,:) = targetdatatrain(random_target(k + size(targetdata,3)-10),:);
                testclass(k,1) = 1;
            end
            if (size(targetdata,3)-10)/2 < round((size(targetdata,3)-10)/2)
                for k = 1:round((size(targetdata,3)-10)/2)
                    data1(k+size(targetdata,3)-10,:) = nt1datatrain(random_nt1(k),:);
                    classes1(k+size(targetdata,3)-10,1) = -1;
                end
                for k = 1:10
                    test(k+10,:) = nt1datatrain(random_nt1(k + round((size(targetdata,3)-10)/2)),:);
                    testclass(k+10,1) = -1;
                end
                for k = 1:round((size(targetdata,3)-10)/2)-1
                    data1(k+(size(targetdata,3)-10)+round((size(targetdata,3)-10)/2),:) =
nt2datatrain(random_nt2(k),:);
                    classes1(k+(size(targetdata,3)-10)+round((size(targetdata,3)-10)/2),1) = -1;
                end
                for k = 1:10
                    test(k+20,:) = nt2datatrain(random_nt2(k + round((size(targetdata,3)-10)/2)-1),:);
                    testclass(k+20,1) = -1;
                end
```

```
        else
            for k = 1:(size(targetdata,3)-10)/2
                data1(k+size(targetdata,3)-10,:) = nt1datatrain(random_nt1(k),:);
                classes1(k+size(targetdata,3)-10,1) = -1;
            end
            for k = 1:10
                test(k+10,:) = nt1datatrain(random_nt1(k + (size(targetdata,3)-10)/2),:);
                testclass(k+10,1) = -1;
            end
            for k = 1:(size(targetdata,3)-10)/2
                data1(k+(size(targetdata,3)-10)+((size(targetdata,3)-10)/2),:) = nt2datatrain(random_nt2(k),:);
                classes1(k+(size(targetdata,3)-10)+((size(targetdata,3)-10)/2),1) = -1;
            end
            for k = 1:10
                test(k+20,:) = nt2datatrain(random_nt2(k + (size(targetdata,3)-10)/2),:);
                testclass(k+20,1) = -1;
            end
        end
    end

    % a linear SVM is used with a C parameter of 10
    net = svm(size(data1, 2), 'linear', [], 10);
    net = svmtrain(net, data1, classes1);
    predictedY = svmfwd(net, test);

    % calculate predictions
    e = abs(predictedY - testclass);
    mce = mean(e);
    t_correct = 0;
    true_negative = 0;
    true_positive = 0;
    false_negative = 0;
    false_positive = 0;
    for t = 1:length(predictedY)
```

```
            if predictedY(t) < 0 && testclass(t) == -1
                t_correct = t_correct + 1;
                true_negative = true_negative + 1;
            elseif predictedY(t) > 0 && testclass(t) == 1
                t_correct = t_correct + 1;
                true_positive = true_positive + 1;
            end
            if predictedY(t) < 0 && testclass(t) == 1
                false_negative = false_negative + 1;
            elseif predictedY(t) > 0 && testclass(t) == -1
                false_positive = false_positive + 1;
            end
        end
        channelssingle = cat(2,channelssingle,t_correct);
        true_n = cat(2,true_n,true_negative);
        true_p = cat(2,true_p,true_positive);
        false_n  = cat(2,false_n,false_negative);
        false_p = cat(2,false_p,false_positive);
        iteration = r
    end
    channels = channels + channelssingle;
    truen = truen + true_n;
    truep = truep + true_p;
    falsen = falsen + false_n;
    falsep = falsep + false_p;
    amounttotal = amounttotal + length(predictedY);
end
percent_correct = channels/amounttotal;
percent_specificity = truen./(truen + falsep);
percent_sensitivity = truep./(truep + falsen);
PPV = truep./(truep + falsep);
NPV = truen./(truen + falsen);

max_perc = max(percent_correct);
```

```
max_classification(1,1) = max_perc;
max_channel(1,1:size(find(percent_correct == max_perc),2)) = find(percent_correct == max_perc);

results = [percent_correct; percent_specificity; percent_sensitivity; PPV; NPV; max_classification; max_channel];
```

Table M.1 Determination of the C-value to be used to maximise classification accuracy (conducted on a test set of data from subject 1). One C-value was chosen for all classifications (however improved accuracies can be obtained by determing the best value per paradigm). A C-value of 10 was chosen due to it having the best all-round result.

C-value	**0.1**	**1**	**10**	**100**	**1000**
No signal processing	3	2	1	4	5
PCA	1	1	1	1	1
PCA and ICA	3	5	2	5	4
PCA and ICA*	4	1	3	4	3
	11	9	7	14	13

Appendix N Principal and Independent Component Analysis

N.1 Principal Component Analysis

PCA falls under a class of subspace projections in multivariate analysis. Signal processing techniques ultimately aim at separating 'signal' from 'noise'. EEG consists of multiple variables combining to form signal mixtures which we see as fluctuations of voltage per time. In most forms of data collection, a multivariate set of data is obtained in which a number of components carry the value of more than one measurement. Thus a method of analysis needs to be determined so as to extract relevant information from these signal mixtures (Krzanowski 1988).

It is a useful method of finding patterns in data with high dimension (face recognition and image compression). It enables the data to be represented in such a way as too highlight similarities and differences. PCA can compress the data without losing too much information (Smith 2002). A simple technique used to perform PCA is as follows:

- Acquire the data
- Subtract the mean
- Calculate the covariance matrix
- Calculate the eigenvectors and eigenvalues of the covariance matrix
- Choose components and form a feature vector
- Derive the new data set

Note: It is possible to retrieve the old data if all the eigenvectors were used in the transformation (otherwise some information is lost).

Mathematically, the *jth principal component* is the linear combination $Y_j = \boldsymbol{a}_j'\boldsymbol{X}$ which has the greatest sample variance for all $\boldsymbol{a}_j$ satisfying $\boldsymbol{a}_j'\boldsymbol{a}_j = 1$ and $\mathbf{a}_j'\mathbf{a}_j = 0\ (i < j)$. The *coefficients* $\boldsymbol{a}_j'$ are given by the elements of the eigenvector corresponding to the *j*th largest eigenvalue l_j of the covariance matrix, and $\text{var}(Y_j) = l_j$. If $\boldsymbol{a}_j' = (a_{j1}, a_{j2}, \ldots, a_{jp})$, then $a_{jk}\sqrt{(l_j)}$ is sometimes called the *loading* of the *k*th original variable on the *j*th component. Finally, if $\boldsymbol{x}_i' = (x_{i1}, x_{i2}, \ldots, x_{ip})$ are the values of the original *p* variable on the *i*th individual, then that individual's value on the *j*th principal component is computed as:

$$y_{ij} = \boldsymbol{a}_j'\boldsymbol{x}_i = a_{j1}x_{i1} + a_{j2}x_{i2} + \ldots + a_{jp}x_{ip}\ (j = 1, \ldots, p) \quad (11)$$

,

This is known as the *i*th individual's *score* on the *j*th component (Krzanowski 1988).

The principal components in any application are defined to be the new variables $Y_i\ (i = 1, \ldots, p)$ that are derived as linear combinations $\boldsymbol{a}_i'\boldsymbol{X}$ of the original variables, while the elements of $\boldsymbol{a}_i$ are called the coefficients of the *i*th principal component (Krzanowski 1988).

PCA decomposes a set of signal mixtures into a set of uncorrelated signals with Gaussian distribution. The assumption that signals from different processes are uncorrelated, but uncorrelated signals are not necessarily from different processes highlights the essential difference between the two and the superceding advantages of ICA over PCA (ICA separates the signal mixtures into independent sources). "A lack of correlation is a weaker property than independence" (Stone 2004).

PCA has been formulated as a suitable projection method for viewing a high-dimensional set of (quantitative) data in a few dimensions – a term known as dimensionality reduction. The important feature of PCA is that it presents a method of compressing the high resolution data into a format for ICA to extract the required information. Thus this increases the analysis' computational efficiency.

N.2 Independent Component Analysis

ICA is a means of separating or filtering useful information from data. It operates by extracting from a set of signal mixtures a set of signal sources dependent on underlying factors. The sources must be linearly mixed (Delorme 2007). These factors are dependent on the processes that produced the signal sources. In essence the measured signals are "a mixture of these underlying factors" (Stone 2004). It is a method of BSS where information may be extracted even if little is known about the sources. The features are statistically independent from one another. The concept follows that "ICA separates signal mixtures into statistically independent signals. If the assumption of statistical independence is valid[45] then each of the signals extracted by ICA will have been generated by a different physical process, and will therefore be a desired signal" (Stone 2004).

It uses the ideas of independence, normality, and complexity to separate the desired signals i.e. signal mixtures are not statistically independent, have normal or Gaussian histograms, and have equal or greater complexity than their simplest constituent source signal. In summary, if source signals have a certain property X, whereas the signal mixtures do not, then an attempt must be made to extract signals with as much X as possible, thereby extracting the source signals. This follows the principle that if signals are independent, have non-Gaussian histograms (abnormal distribution), and have low complexity they represent the source signals of the mixture. An important factor is that there must be at least as many mixtures as there are source signals. In EEG the number of different signal mixtures is equal

[45] "… if statistically independent signals can be extracted from signal mixtures then these signal mixtures must be from different physical processes…" (Stone 2004).

to the number of electrodes and the number of sources (or waveforms contributing to the desired output) is typically much less than this in a high resolution system. Pre-processing methods may be used to reduce the number of signal mixtures by specifying the number of sources or using PCA (Stone 2004).

Mathematically, recorded EEG data is represented by the vector $x_i = (x_1, \ldots, x_m)$ made up of components represented by the vector $s = (s_1, \ldots, s_n)$. Here it is assumed that $n \geq m$. The aim is to transform the observed data x, using a transformation W as $s = Wx$, into maximally independent components s measured by some function $F(s_1, \ldots, s_n)$ of independence. In other words assume that we record n linear mixtures $x_1, \ldots, x_n$ of n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \ldots + a_{jn}s_n, \qquad (12)$$

for all j, where $A = (a_{j1}, \ldots, a_{jn})$ and $A^{-1} = W$. Without loss of generality, we can assume that both the mixture variables x_i and the independent components s_i have zero mean. If this is not the case, then the mixture variables can always be centred by subtracting the sample mean, which makes the model zero-mean (Hyvarinen, Oja 2000).

All vectors are understood as column vectors; thus the transpose of x, x^T, is a row vector. Thus the mixing model can be written as $x = As$ (Groppe, Makeig & Kutas 2008). This can also be written as:

$$x = \sum_{i=1}^{n} a_i s_i \ . \qquad (13)$$

It is important to note that the starting point for ICA is the very simple assumption that the components s_i are statistically *independent* and that the independent components have *non-Gaussian* distribution. With these assumptions the task is to estimate the mixing matrix A and the source signals s. The original sources s can be recovered by multiplying the signal mixtures x by the inverse of the mixing matrix $W = A^{-1}$, also called the unmixing matrix i.e. $s = Wx$ (Hyvärinen, Oja 1999).

Appendix O Example of Averaged ERP

An example of the averaged ERP from the traditional paradigm for subject 10 is shown in Figure O.1. The progression of the P300 from Fz (channel 11) to Cz (channel 129 or the ‘reference’ channel) to Pz (channel 62) is evident. The timeframe is from the stimulus onset to 650 ms (as per the method of feature extraction described in Chapter 3).

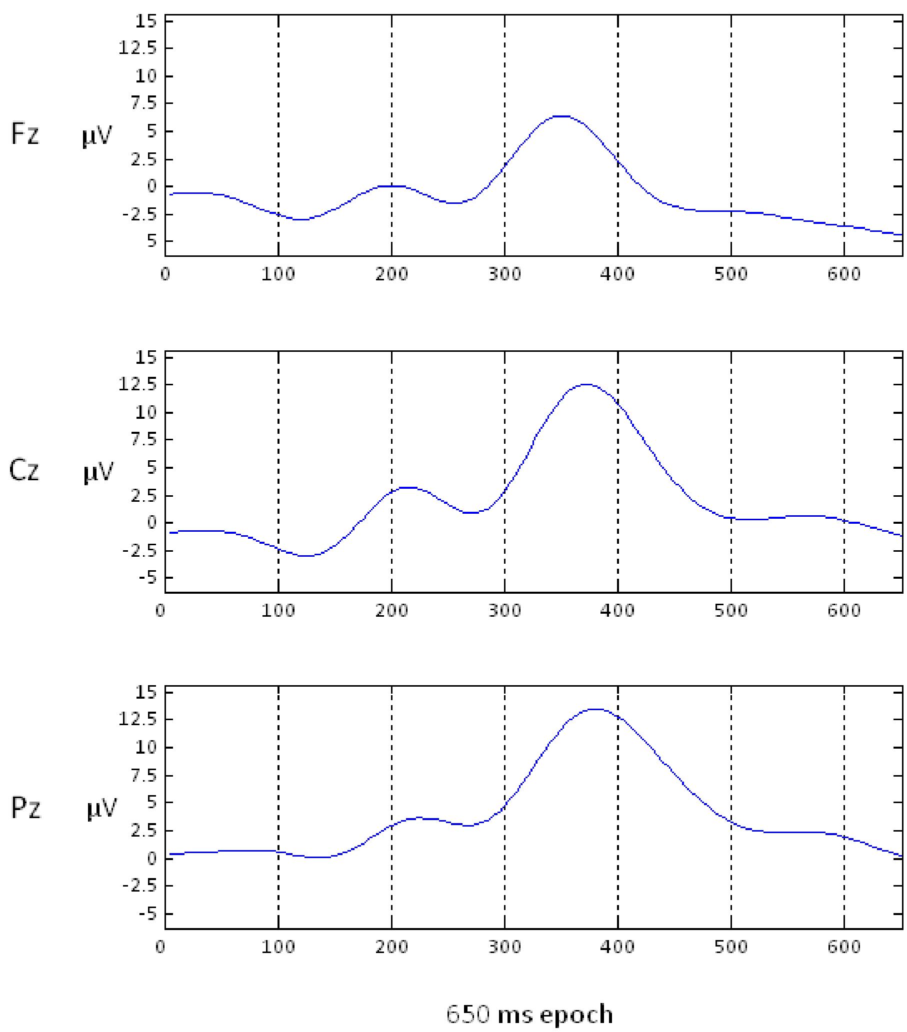

Figure O.1 Averaged ERP from subject 10 traditional paradigm.

Appendix P Support Vector Machines for Classification

Once the appropriate EEG epochs have been selected post the signal processing techniques employed to highlight or extract the data, they need to be presented to a classifier for classification. This is the decision medium within the BCI which is able to discriminate between relevant and irrelevant information. There exist both linear and non-linear classifiers, including Linear Discriminant Analysis (LDA), Hidden Markov Classifier, z-scale base Discriminant Analysis (ZDA), artificial neural networks (ANN), the extreme learning machine (ELM), nearest neighbour classifier, and SVMs. A primitive, but sometimes effective, example of a classifier is an amplitude threshold classifier, where time positions in robust waveforms are monitored for values above and below the threshold i.e. they classify waveforms according to their inherent value at a predetermined time position.

SVMs can also be used for feature elimination (they discard features that give poor classification results) (Cristianini, Shawe-Taylor 2000). In most instances the SVM is able to outperform many classification algorithms for BCI applications. They operate by learning a classification function from training data, and do not require pre-defined rules to function as a classifier (Thulasidas, Guan & Wu 2006). Due to the complexity of the signal post processing, the SVMs ability to 'learn' and its relative success for categorisation within the BCI literature, SVM becomes an attractive method to classify EEG waveforms (Cabrera, Farina & Dremstrup 2010).

Classification tasks usually involve training and testing of data. The data consists of data instances which contain one target value (class label) and several attributes (features). Ultimately the goal of a SVM is to produce a model which predicts the class label of the data instances in a test set which is only given the features.

Given a training set of instance-label pairs $(x_i, y_i), i = 1,\ldots,l$ where $x_i \in \Re^n$ and $y \in \{1,-1\}^l$, the SVMs require the solution of the following optimisation problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C\sum_{i=1}^{l} \xi_i , \tag{14}$$

subject to $y_i\left(w^T \phi(x_i) + b\right) \geq 1 - \xi_i$, where $\xi_i \geq 0$.

Training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function ϕ. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty parameter of the error term. Furthermore, $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function. New kernels are proposed, but the four standard kernels are:

- linear: $K(x_i, x_j) = x_i^T x_j$.
- polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$.
- radial basis function (RBF): $K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \gamma > 0$.
- sigmoid: $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$.

Here γ, r and d are kernel parameters (Gunn 1998).

SVMs are supervised learning systems that use a hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimisation theory that implements a learning bias derived from statistical learning theory. It formulates a computationally efficient way of learning appropriate separating hyperplanes in high dimensional feature space, by controlling the hyperplane margin measures (Cristianini, Shawe-Taylor 2000). The simplest model is the maximal margin classifier which works for data that can be separated linearly. It minimises the classification error by separating the data with a maximal margin hyperplane (see Figure P.1).

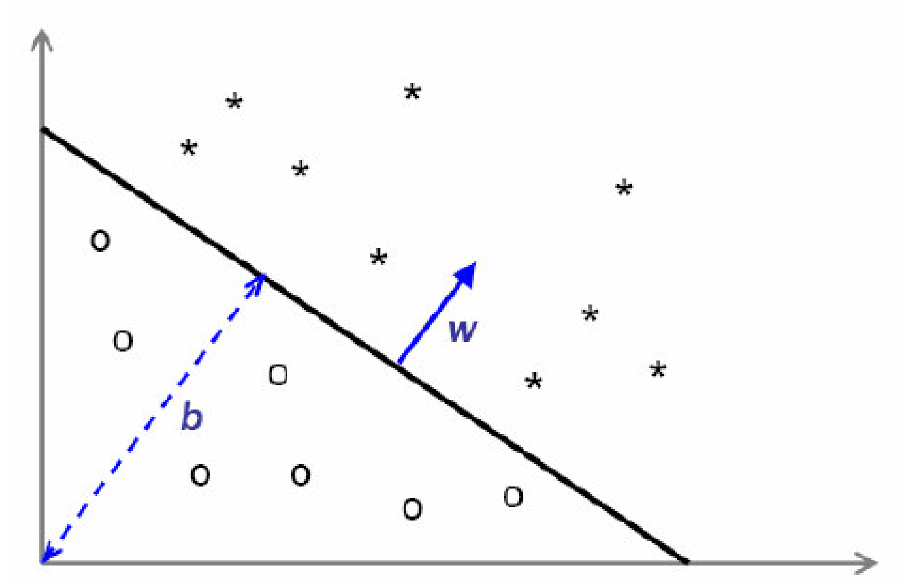

Figure P.1 A separating hyperplane (w,b) for a two-dimensional training set (Cristianini, Shawe-Taylor 2000).

There are many possible linear classifiers that can separate the data, but there is only one that maximises the margin i.e. the distance between it and the nearest data point of each class. This hyperplane (separating the data) is termed the optimal separating hyperplane (Gunn 1998). The maximum margins of this hyperplane are defined by the nearest points of each class and are termed the support vectors (see Figure P.2). These contain all the information needed for classification and may be used to summarise large datasets. Ultimately the hyperplane determines in which class the stimulus falls.

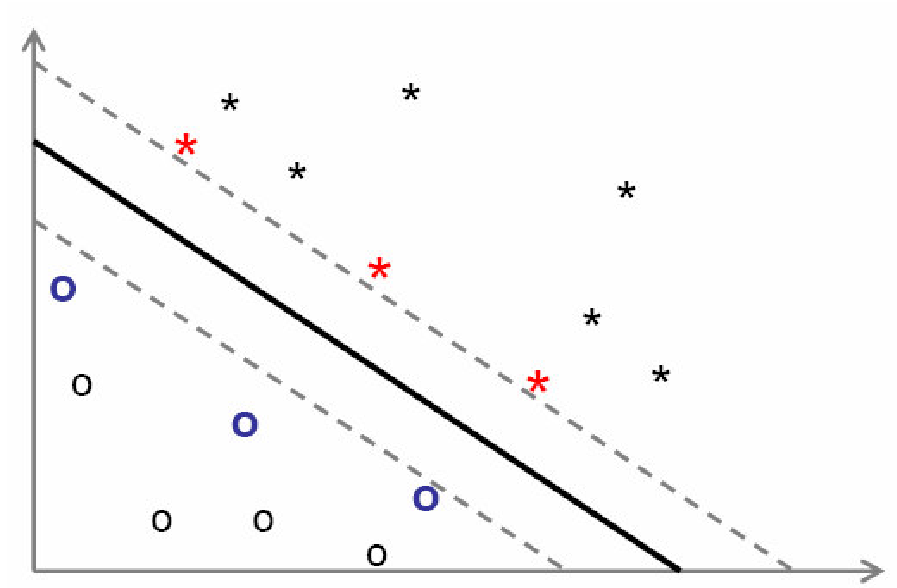

Figure P.2 The maximal margin hyperplane with its support vectors highlighted (Cristianini, Shawe-Taylor 2000).

Appendix Q Example of classification accuracies across channels

Table Q.1 Example of classification accuracies of all channels for the auditory multi-class paradigm with button pushing (subject 1).

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
50.7%	54.3%	51.3%	58.7%	61.7%	63.3%	62.3%	63.7%	60.0%	56.0%
11	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
61.0%	62.7%	62.0%	64.7%	59.0%	62.0%	57.0%	63.3%	59.3%	64.3%
21	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
64.0%	55.7%	64.3%	58.3%	61.7%	61.7%	58.7%	55.0%	56.0%	63.0%
31	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
63.3%	62.7%	56.7%	53.0%	57.0%	56.3%	59.7%	64.0%	49.0%	54.7%
41	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**
52.3%	57.7%	58.3%	52.3%	46.7%	43.0%	48.0%	48.3%	40.3%	44.0%
51	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**
49.0%	56.0%	60.0%	63.0%	63.3%	48.7%	43.3%	45.3%	51.0%	60.0%
61	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**
59.7%	62.7%	53.0%	44.7%	40.3%	55.7%	59.7%	57.3%	49.3%	51.3%
71	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**
46.7%	52.0%	56.3%	51.7%	51.3%	52.3%	51.7%	55.0%	61.0%	65.7%
81	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**
63.7%	62.7%	55.3%	53.0%	57.3%	57.3%	60.0%	61.3%	56.0%	56.7%
91	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**100**
53.7%	60.3%	56.3%	61.3%	54.3%	58.3%	58.0%	56.7%	58.3%	50.0%
101	**102**	**103**	**104**	**105**	**106**	**107**	**108**	**109**	**110**
60.7%	60.0%	55.7%	57.3%	59.7%	62.0%	63.0%	50.3%	54.0%	59.0%
111	**112**	**113**	**114**	**115**	**116**	**117**	**118**	**119**	**120**
57.3%	59.7%	59.7%	47.3%	50.0%	51.0%	53.3%	58.0%	59.7%	47.0%
121	**122**	**123**	**124**	**125**	**126**	**127**	**128**	**129**	
54.7%	49.3%	55.3%	52.3%	57.0%	48.3%	49.7%	51.0%	60.7%	