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Investigation into BCI illiteracy and the use of BCI for relaxation

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by

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Abstract

Brain-computer interface (BCI) allows for communication between a human and a machine without the use of normal output pathways (e.g. muscles and peripheral nerves), however a substantial number of people are unable to effectively control BCI devices. In this thesis we present two BCI investigations. In experiment one we investigate the use to commercially available BCI system for relaxation. A number of studies investigated the factors affecting BCI illiteracy, however no research into psychological and cognitive factors of BCI performance has been conducted. In experiment two, we investigate the relation between BCI illiteracy and attention. The results of the first experiments show that the participants using BCI as neurofeedback did not obtain higher level of relaxation then the participants watching video or sitting with their eyes closed. The results of the second experiments showed no connection between BCI illiteracy and attention.

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Chapter 1

Introduction

Brain-computer interface (BCI) allows users to control computer by using their thoughts. BCI systems decode users' thoughts and translate them into commands that are understandable to a machine. BCI applications include communication, motor restoration, locomotion, environmental control, entertainment and other. BCI systems can also be used as biofeedback to provide users with alternative means of relaxation or attentional training, however not everyone is able to control a BCI system and this phenomenon is called BCI illiteracy. It is not obvious how psychological and cognitive factors such as attention affects the user's ability to control BCI devices. As mentioned above BCI technology can be used for relaxation and attentional training, it is however unknown if off-the-shelf BCI systems can be successfully used for these purposes.

1.1 Motivation

BCI is a new and exciting technology. Numerous applications for this technology have been proposed (see section 2.9). A substantial proportion of the potential users are, however unable to control a BCI device. This phenomenon is called BCI illiteracy. Understanding the factors the determine BCI performance and BCI illiteracy is crucial for continued development and popularisation of this technology. If BCI is to become popular across the wider population it is also important that off-the shelf, commercial devices can bring benefits to end users. Our motivation can be summarised in the two following research questions.

1.1.1 Is attention a factor influancing BCI performance and BCI illiteracy?

Understanding the role played by attention, and our ability to control these it is crucial for the development of BCI systems. BCI illiteracy is a complex symptom, not only reflecting contextual effects (whether the user actually care to perform well), but also due to fundamental differences in our abilities to control, steer and focus our attention on events in the environment. In this thesis we investigate if attentional abilities play a role in BCI performance. We investigate this question in experiment 2.

1.1.2 Can off-the-shelf BCI systems be used for relaxation?

As mentioned above, a number of sophisticated BCI systems have been proposed for training of attention. In similar manner we investigated if, off-the-shelf Emotiv EPOCH system can be used to induce a state of relaxation in the user. We try to answer this question in experiment 1.

1.2 Contributions

This thesis investigates two important aspects of BCI: the determinants of BCI illiteracy and the use of commercial BCI system to induce a state of relaxation. However, both performed studies did not provide significant results.

1.3 Outline of the Thesis

In chapter 2, we present a literature review concentrating on different types of BCI systems, neurological basis for EEG recordings, the phenomenon of BCI illiteracy, models of attention and the connections between attention, meditation and BCI performance. In chapter 3, an experiment investigating the use of BCI systems as neurofeedback to obtain a greater level of relaxation is presented. In chapter 4, we describe an experiment investigating the connection between the attention, measured by two behavioural tasks, and performance on

P300-based BCI. In chapter 5, considerations for future investigations are presented.

Chapter 2

Background

2.1 Introduction

In this chapter we present a literature review concentrating on different types of BCI systems, neurological basis for EEG recordings, the phenomenon of BCI illiteracy in different BCI paradigms, the models of attention and the connections between attention, meditation and BCI performance.

2.2 What are Brain-Computer Interfaces?

A brain computer interface (BCI), also known as brain-machine interface (BMI) is a system that allows for direct communication between a human and a machine without using traditional channels of interaction, e.g. the muscles of the arm and hand and computer keyboard, and instead relies on brain signals directly (Wolpaw et al., 2002). This fact makes BCI technology especially attractive for people with severe motor disabilities such as multiple sclerosis (MLS) or locked-in syndrome (LIS). In extreme cases such interface is the only way by which a person can communicate with the external world, which can greatly improve their quality of life. The idea of BCI was initially unattractive to science, the idea of deciphering human thoughts seemed weird and remote. BCI systems were limited to laboratory and clinical use; however the recent developments in machine learning technology and increase in computational power of personal computers made BCI accessible not only to researchers and clinicians, but also for everyday users. The number of research groups investigating BCI technology, as well as the number of published articles has increased substantially over the last decade.

BCI is an artificial intelligence system that employs machine learning. Such a system consists of hardware and software components with the aim of recognising patterns in the signals emitted by the brain, and to translate them into practical commands. In a typical BCI system, five consecutive stages can be identified (Nicolas-Alonso and Gomez-Gil, 2012).

1. Signal acquisition - various types of signal are captured by a neuroimaging device such as electroencephalography (EEG); a BCI system may be acquiring several kinds of signals at the same time, provided they are synchronised and time-locked to the interaction

with the device.

2. Signal pre-processing or signal enhancement - signal is prepared to further processing, including artefact removal (e.g. muscle movement and noise reduction) are typically performed at this stage.

3. Feature extraction - discriminative features are identified and then mapped onto a vector; these may include first order parameters, like amplitude of signal or latency, and second-order parameters that require more processing, like time-frequency parameters extracted from a Fourier transform.

4. Classification - involves the categorisation of the features previously extracted, with the aim of ascribing meaning to them; various techniques from machine learning can be applied and these are described in more detail in section 2.8.

5. Control interface - results of classification are translated into commands and send to a connected machine such as a wheelchair or a computer, which provide the user with feedback and close the interactive loop between the user and the device.

2.3 Classification of BCI systems

Different types of BCI systems have been proposed. These types can be classified according to a number of criteria: place of signal acquisition, type of measured brain activity, requirement of sensory stimulation to elicit brain activity, the presence of a cue determining the onset, offset and duration of operations. Classification according to the mentioned criteria is presented below.

2.3.1 BCI systems according the place of signal acquisition

Two approaches can be identified in this category: invasive and non-invasive. In case of invasive approach the signal is acquired using electrodes placed inside the scalp. The electrical activity of single neurons (intracortical neuron recording) or neural assemblies (electrocorticography) is recorded. This method is used mainly to re-establish interrupted connections (e.g. people with paralysis or locked-in syndrome, use voluntary motor signals in order to control a prosthetic limb (Lebedev and Nicolelis, 2006). The main advantage of this approach is the good quality of signal and the possibility to acquire the signal of good special resolution from selected cortical areas of the brain (e.g. motor cortex in case of prosthetic limb). Many researchers agree that restoration of limb movement with multiple degrees of freedom can only be achieved through invasive BCI. However, the invasive methods require open skull surgery which poses serious health risks and restricts their use to clinical and experimental settings.

In non-invasive BCI the signal is acquired outside of the scalp. Different indicators of brain activity as well as different neuroimaging techniques can be used for signal acquisition and these are described in section 2.3.4.

2.3.2 BCI systems according to the requirement of sensory stimulation

In this category we can distinguish two types of BCI systems: dependent and independent. BCI does not use neural pathway and muscles to communicate the signal from the brain to the computer or machine, however dependent BCIs really on external stimulation, sensory organs and neural pathways to elicit brain activity that is later measured and recoded to a command that is passed to a machine. Examples of dependent BCI paradigms include P300 and SSVEP. In SSVEP-based BCIs (Cheng et al., 2002), a flickering stimuli is necessary to elicit an EEG response of the same frequency or harmonics of that frequency. In BCI systems employing P300 paradigm, visual or auditory stimuli must be presented in order to produce P300 response (Mugler et al., 2010; Furdea et al., 2009).

In case of independent BCIs the engagement of sensory organs, peripheral nerves and muscles is not needed. Most examples of independent BCI are based on sensorimotor rhythms (SMR) (Pfurtscheller et al., 1993) slow cortical potentials (SCP) (Hinterberger et al., 2004) and non-motor imagery (Curran et al., 2004; Cabrera and Dremstrup, 2008).

2.3.3 BCI systems according to the presence of a cue

Synchronous BCI systems are cue based, which means that they depend on a protocol to determine the onset, offset and the duration of the operations. The appearance of a cue informs the subjects about the task they are to perform. An example of this kind of BCI is a system where the participant sitting in front of a computer is asked to move the cursor to the left or to the right of the screen. Left hand imagery moves the cursor to the left and right hand imagery moves it to the right. The appearance of the target on the left or right side of the screen informs the user which mental activity to perform. Examples of synchronous systems can be found in (Allison et al., 2008; Donchin et al., 2000).

On the other hand, asynchronous BCIs are always active and search for predefined activation patterns of the brain associated with mental operations performed by the user, which inform the machine to perform certain action. These types of systems can also detect an idle state when the participants are not trying to control the BCI and are not performing any predetermined mental activities. In this case the system does not provide feedback. Examples of asynchronous systems can be found in Bashashati et al. (2006) and Fatourechi et al. (2008).

2.3.4 BCI systems according to the type of recorded brain activity

There are two types of brain activity that can be used for this purpose: metabolic and electromagnetic. Only the latter type of systems is currently available for day-to-day BCI devices. For each of the brain activity modalities there are two different neuroimaging techniques that can be used. These methods are discussed below.

BCI based on metabolic brain activity

In case of BCI systems that use changes in metabolic brain activity as a source of signal, there are two technologies that are currently utilized: functional magnetic resonance imaging (fMRI) and functional near infrared spectroscopy (fNIRS). They both rely on very different method of signal acquisition, and are consequently sensitive to very different variations in the signal. fMRI is primarily used in research, because it is not practical for day-to-day use, whereas fNIRS, which may be more accessible to a wider audience, is still under development.

fMRI measures brain activity by detecting associated changes in blood flow (Huettel et al., 2004). This technique utilizes the fact that the neural activity and cerebral blood flow are coupled. In response to the increased brain activity in a certain area, the blood flow to that brain area increases (haemodynamic response) in order to supply the stressed neural tissues with nutrients such as oxygen and glucose and allow them to function. This supply of highly oxygenated blood causes change in the magnetic field which is recorder by MRI scanner.

A number of fMRI-based BCI systems have been developed, that include spelling machines (Sorger et al., 2012), computer games (Yoo et al., 2004; Peplow, 2004), and systems controlling robotic arms (Nam et al., 2013). Goebel developed a system in which two participants could play a computer ping pong game while in the scanner (Peplow, 2004). Another fMRI-based BCI game has been proposed by Yoo et al. (2004) where participants navigate through a two - dimensional labyrinth.

Nam et al. (2013) developed a system that enabled participants to control a robotic arm. To achieve the best control the action has to be delayed by 6 seconds. This shows one of the main limitations of fMRI-based BCI; the low temporal resolution of fMRI end the temporal delay of haemodynamic response limits the throughput that can be achieved using these systems. The information transfer rate in fMRI-based BCIs is between 0.60 and 1.20 bits/min (Ward and Mazaheri, 2008) as compare approximately 4 bits/min for fNIRS-based BCI (Power et al., 2011) and can reach up to 60 bits/min for EEG-based BCI (Wolpaw et al., 2000). Secondly, MRI scanners are very large, expensive, require specially prepared room and the participants have to be lying down while using the scanner. The above limitations restrict the use of this kind of devices to clinical settings and research (e.g. rehabilitation).

fNIRS uses the properties of near-infrared light in the spectrum of 700-900 nm to assess the level of oxygenated versus deoxygenated haemoglobin in the cerebral blood. The scalp and bone tissue are invisible to the near-infrared light, however the oxygenated and deoxygenated haemoglobin absorbs the light of a different wave length at a different rate. Therefore, by using the two different wave lengths the relative concentration of oxygenated to deoxygenated haemoglobin can be calculated (Jobsis, 1977). The light is emitted to the brain by an infrared light emitting diode (IRED) and the reflected light is detected on the scalp. Due to the shallow penetration of the light to the brain this technique is limited to the outer cortical layer.
Although fNIRS has been adapted to the BCI research fairly recently (Coyle et al., 2007, 2004) and at the moment the information transfer rate achieved using this method is relatively low (Power et al., 2011). It may, however be increased in the future and this method is a promising alternative to the most popular EEG-based BCI, which, due to its limitations cannot be used with certain groups of people (for more see 2.10).

BCI based on electromagnetic brain activity

There are two methods that measure electrical brain activity from outside of the skull. These are magnetoencephalography (MEG) and electroencephalography (EEG). They are both based on the same neurophysiological mechanisms but measure complementary signals, namely magnetic fields and electrical potentials, respectively.

MEG is a non-invasive imaging technique that registers changes in magnetic field associated with the electrical activity within the brain (Waldert et al., 2009). MEG and EEG record signal associated with the same neurophysiological processes. However, the magnetic field is less prone to distortions introduced by the skull and the scalp than the electric field (Salmelin et al., 1995), therefore the quality of signal provided by the MEG is better than in case of EEG. MEG provides better spatio-temporal resolution, which leads to reduced training time needed to attain satisfactory control and makes it a useful technique for BCI (Mellinger et al., 2007). Lal et al. (2005) presented the first online MEG-based BCI that allowed subjects to write a short name using movement imagery. Other MEG-based BCI systems have been proposed (Kauhanen et al., 2006; Georgopoulos et al., 2005; Mellinger et al., 2007; Sabra and Wahed, 2011; Zhang et al., 2011), however this method is still in its early stage, as compared to EEG-based BCI. The main limitations of MEG-based BCI are similar to the ones of fMRI-based BCI. These include: high cost and large equipment that cannot be used outside of laboratory.

EEG is the oldest and most widely used neuroimaging technique. Since its discovery in 1929 (Berger, 1969), EEG has been used by scientists to answer questions about the functioning of the human brain as well as by clinicians as a diagnostic tool. BCI systems also allow using EEG as neurofeedback in neurorehabilitation. One of the reasons for the popularity of EEG based systems is the relative low cost, portability and low complexity of these systems. EEG recordings are usually performed using small metal electrodes placed on the scalp in standardised positions. The number of electrodes can vary. The electrode configuration is shown in Figure 2.1. Electrode caps are used to affix electrodes to the scalp and ensure that the electrodes stay in place throughout the recording. To improve the conductivity between scalp and electrodes conductive gel or saltwater is used.

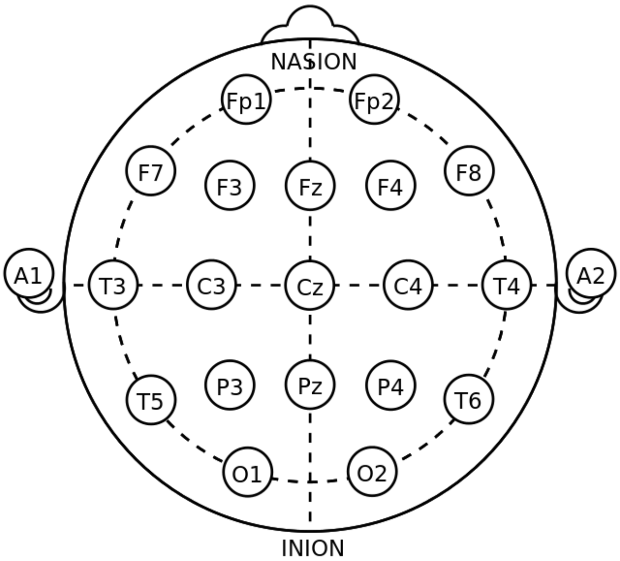

Figure 2.1: Standardised electrodes location according to International 10–20 system.

EEG is the recording of electrical potentials along the scalp. The electrical potentials recorded by EEG result from the neural activation within the brain. EEG is the most widespread neuroimaging technique and the most widely used modality in BCI. The popularity of EEG stands from the fact that electrical signal can be easily and cheaply recorded through electrodes placed on the scalp (Baillet et al., 2001). However, electric current has to cross the scalp, skull and other tissues surrounding the brain which significantly distorts the acquired signal. EEG signal is also distorted by the electrical noise in the environment and electric current produced by muscle activity.

Researches using EEG identified distinctive patterns in the EEG signal. These patterns are related to specific cognitive activities. Although, the exact meaning of most of these patterns is still unknown, some of them have been thoroughly studied and are used in BCI systems. The three EEG signal features that are most often used in BCI research are P300, sensorimotor rhythms and steady state visually evoked potentials. These are described in more detail in sections: 2.10.2, 2.10.1 and 2.10.3.

BCI systems often use alpha frequency band (8–13 Hz), as it is relatively easy to produce (eyes open vs. eyes closed), and is typically emitted when the participant daydreams or falls asleep. It is therefore typically used as a gross measure of attention. As we will see in the following sections, however, attention is a multifaceted cognitive ability that cannot be simplified to one single parameter, like the amplitude of the alpha band, and this parameter should not be used as a direct measure of attention.

As both investigations presented in this thesis use EEG-based BCI system, in the next sections we will discuss the subject of electroencephalography and the neural basis EEG signal in more detail and further describe the elements and stages of EEG-based BCI system: such as feature extraction and classification.

2.4 How is EEG signal generated?

To explain the relation between EEG and information processing in the brain, it is necessary to first describe the structure and functioning of neurons. Neuron is a cell in the nervous system that processes and transmits information using electrical and chemical signals. A typical neuron possesses a cell body (soma), dendrites, and an axon. The cell body can give rise to many dendrites. Dendrites are thin structures that span for hundreds of microns and form a dendritic tree. The cell body can give rise to multiple dendrites, but can produce only one axon, however axons can branch out hundreds of times before they terminate. A human axon can extend for up to one meter. Dendrites and axons connect neurons forming neural networks. Information from one neuron to another is passed through synapses. In most cases a synapse connect an axon to a dendrite, however there are exceptions (e.g. axon can connect directly to the body of the neuron).

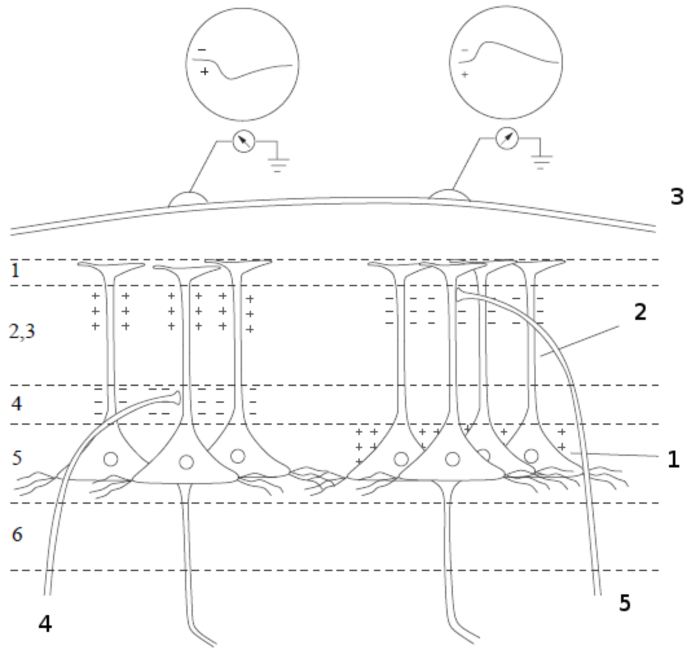

Figure 2.2: Simple representation of brain cortex showing production of EEG signal for activation of excitatory neurons. On the left the axon of the excitatory cell connects to the dendrite close to the soma of the pyramidal cell, which results in positive potential detectable on the scalp. On the right the axon of the excitatory cell connects to the dendrite close to the surface of the cortex, which results in negative potential detectable on the scalp. For historical reasons, the positive potential is shown on the graph as a decrease and the negative potential is shown as an increase. 1 - soma of the pyramidal cell, 2 - apical dendrite of the pyramidal cell, 3 - skull and scalp, 4 and 5 - axons of excitatory neurons. Adapted from Martin (1991)

Neurons communicate through action potentials, i.e. electrical discharge produced by the soma of the cell. Action potential travels along the axon and when the action potential arrives at the synapses neurotransmitter is released. Neurotransmitter triggers change in potential of the membrane of the receiving cell (flow of ions through the cell membrane) and if this potential reaches a threshold, new action potential is triggered and the information is transmitted to another neuron.

The signal measured using EEG equipment is thought to be generated mostly by the pyramidal neurons located in the cerebral cortex (Martin, 1991). Pyramidal neurons have large soma of a shape that resembles a pyramid (see Figure 2.2) and a large dendrite extending from the apex of the soma and is directed perpendicular to the surface of the cortex. Activation of an excitatory synapse creates excitatory post-synaptic potential (i.e. inflow of positively charged ions from the extracellular space to body of the neuron). As a result, the extracellular region of the synapse becomes negatively charged and in turn regions distant from the synapse become positively charged and cause a change of potential (extracellular current) to flow towards the region of the synapse. The spatio-temporal summation of these extracellular currents at hundreds of thousands of neurons with parallelly oriented dendrites creates the change of potential that is detectable on the surface of the scalp. If a large number of excitatory synapses are activated close to the surface of the cortex, the resulting potential, detectable on the surface of the scalp, is negative. If synapses of the same type are activated closer to the body of the pyramidal neurons, deeper in the cortex the resulting potential is positive. Reverse relation is observed for inhibitory synapses. Activation of a large number of inhibitory synapses close to the surface of the brain produces positive potential and activation of inhibitory synapses in the deeper layers of the cortex results in negative potentials recordable on the surface of the scalp. It is therefore possible to infer the type of synapses activated from the polarity of the signal acquired on the surface of the scalp.

2.5 Oscillatory nature of EEG signal

EEG signal collected on the surface of the scalp has an oscillatory nature; it has a sinusoid like form of different frequencies and amplitudes. The frequency of the signal differs depending on the type of activity performed. Over decades researchers recognised frequency bands and connected them with activities or states of the brain. This classification is somewhat conventional and researchers often differ in their definition of these frequency bands. Well known frequency bands and their functional significance are shortly described below (Sanei and Chambers, 2008) and the visual representation of these frequency bands is presented in Figure 2.3.

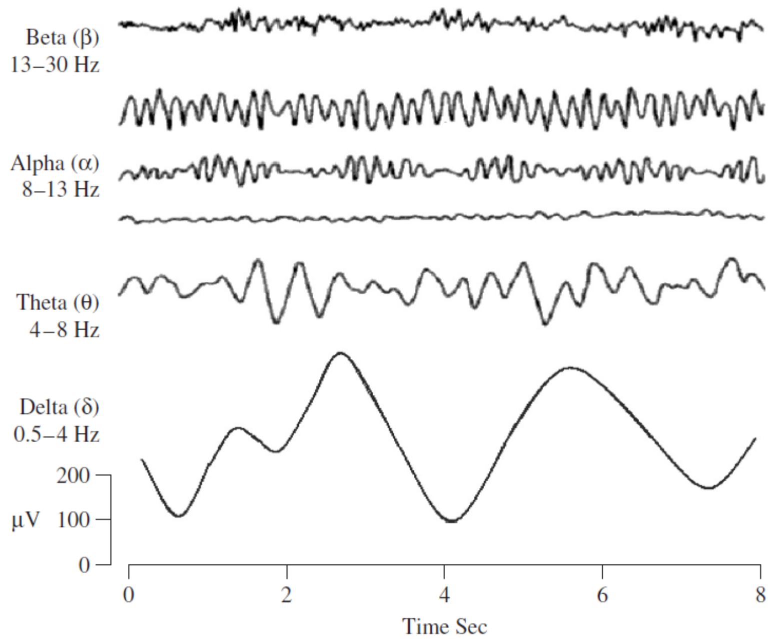

Figure 2.3: Visual representation of alpha, beta, theta and delta EEG frequencies. Adapted from (Sanei and Chambers, 2008).

Delta (0 Hz to 4 Hz) is the highest in amplitude. It is normally seen in adults during sleep and in babies in awake state.

Theta (4 Hz to 7 Hz) is seen normally in young children. In adults and teens is often observed in state of drowsiness and idling, however large contingents of theta frequency in walking adults is likely to have pathological origins. It is also often observed when a person tries to inhibit a response to action. Theta waves are also observed in meditation (Cahn and Polich, 2006).

Alpha (7 Hz to 14 Hz) is the best known and studied EEG frequency band. It is observed in the posterior and occipital regions of the brain. Alpha frequency can easily be induced by closing the eyes or by relaxation. Opening the eyes or performing any mental operation (like calculating or intensive thinking) results in rapid suppression of alpha frequency. The exact origin of alpha frequency is still unknown and some postulate the existence of three different types of alpha waves: one - observed in relaxed state (as mentioned above), second - in REM phase of sleep and third - alpha-delta or slow-wave state (SWS).

Mu (8 Hz to 13 Hz), also called the Rolandic rhythm, overlaps with Alpha frequency. It is believed to reflect the synchronous firing of motor neurons in rest state. It disappears when motor action is observed and this suppression is believed to result from the desynchronisation of motor neurons.

Beta (15 Hz to around 30 Hz) is usually observed symmetrically on both sides of the brain and is mostly evident frontally. It is closely associated with motor behaviour. A suppression of beta wave can be observed during active movement. It is a dominant rhythm in patients who are alert and have their eyes open.

Gamma (30 Hz to 100 Hz) is believed to correspond to binding of different populations of neurons to perform a cognitive or motor task (Niedermeyer and da Silva, 2005).

2.6 Artefacts in BCI

Artefacts are undesired signals that contaminate neurological signal making deciphering user intention more difficult. Artefacts originate from physiological and non-physiological sources. Non-physiological artefacts include power-line noise or changes in electrode impedances, and can be usually avoided by proper filtering, shielding, etc. Physiological artefacts are generated by muscular, ocular and heart activity, known as electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG) respectively. EMG artefacts are usually large disturbances in brain signal caused by muscle activity when participants are talking, chewing or swelling. EOG artefacts are caused by blinking or eye movement. Blinking produces high-amplitude patterns; these are in fact muscle artefacts caused by muscles contractions when participants blink. The artefacts caused by eye movement are of low-frequency and are caused by the different polarisation of the retina and the cornea. EOG artefacts are most pronounced in the frontal area due to the spacial proximity of the eyes. ECG artefacts introduce to the EEG a rhythmic signal which reflects the activity of the heart. Changes in signal produced by brain activity can also be considered as artefacts. For example, in P300-based BCI, a visual evoked potential (VEP) does not contribute to the signal and removing it is likely to provide better signal-to-noise ratio; it can, therefore also be considered an artefact. Similarly, visual alpha rhythms that appear in a Mu-based BCI system can contaminate the signal and should be treated as artefacts (McFarland et al., 1997). Handling physiological artefacts is more challenging than non-physiological artefacts and three approaches to the artefact problem are presented below.

2.6.1 Artefact Avoidance

The simplest method of handling artefacts is to avoid them by issuing proper instructions to the user. Many artefacts are produced by voluntary muscle movements. Subjects can be instructed to avoid blinking or moving their body during the experiments. This method has one very simple advantage - it does not create any computational demands, as it is assumed that the artefacts are not present in the signal. Some physiological activities, such as heart beat are involuntary; therefore this method cannot be applied to this type of contamination. It is not easy to control eye and other movements during the process of data acquisition and different participants can present differing degrees of control, we therefore cannot be sure if the signal is contaminated and how much, moreover collecting sufficient amount of data without artefacts in participants with neurological disabilities is very difficult (Vigário, 1997). Avoiding artefacts introduces another cognitive task which can interact with the BCI task. It has been shown that refraining from eye blinking results in changes in the amplitude of some evoked potentials (Ochoa and Polich, 2000).

2.6.2 Artefact Rejection

Another approach to the problem of artefacts is artefact rejection. In this case, epochs where the brain signal is contaminated with particular artefact are discarded. This procedure can be performed manually - by visual inspection as well as automatically.

Automatic artefact rejection approach is far less labour intensive and time consuming than manual approach and can be therefore applied in real-time BCI system. However, automatic rejection still suffers from sampling bias and loss of valuable data (Ramoser et al., 2000). If EMG signal is collected, epochs where EMG signal reaches a predetermined threshold can be removed. However, many BCI systems, especially those commercially available, do not provide the means of EMG acquisition, therefore contaminated epochs have to be identified and rejected relaying on EEG signal only. Because of the large amount of artefact that exist in BCI systems it is impossible to reject all the contaminated epochs and in practice only the signal with the largest artefacts is rejected.

Rejecting artefacts in off-line analysis, where the continuity of the data is not so important can be very useful in providing cleaner data. However, using artefact rejection in on-line systems creates an important problem. Rejection of signal creates a period of time in which the communication between the human and the device is broken and the system is unresponsive. This provides a false feedback to the user and decreases the fluency of BCI control. On the other hand, if the artefacts are not handled false positive classifications may occur, which is very frustrating and decreases the level of BCI control.

2.6.3 Artefact Removal

Artefact removal attempts to remove artefact from the brain signal while leaving as much of the signal related to the relevant brain activity intact. A number of methods of artefact removal have been proposed and the most popular of them are shortly described below.

Linear Filtering

Linear filtering is a useful method of artefact removal if the signal of interest is in the different frequency band than the artefacts signal (Gotman et al., 1973). Low-pass and high-pass filters can be distinguished. In simple terms, low-pass filters remove the signal above a certain frequency and high-pass filters remove signal below a desired frequency.

Linear filtering is a relatively simple method. It does not require any additional information regarding EMG and EOG activity. This method cannot, however be used when the frequency of the signal of interest lies in the same frequency band than the artefacts (de Beer et al., 1995) and this is often the case in BCI, which means that the use of linear filtering may result in removal of the signal of interest. If the frequency of the artefact and the frequency of the signal overlap, compromise can be made and appropriate cut-off points can be found that allow to remove parts of the artefact and preserve the signal of interest. EOG artefacts consist of low-frequency components, therefore using high-pass filter will remove large part of these artefacts. This filter can be used in systems that rely on features extracted from high frequency components of the EEG signal, such as Mu and Beta rhythms. For EMG artefacts, which consist of high-frequency components, low pass filter can be used.

Regression

The most popular method of artefacts removal is the use of linear combination of EOG-contaminated EEG signal and the EOG signal (Croft and Barry, 2000). It is assumed that EEG signal collected on the scalp is a linear combination of signals resulting from brain activity and EOG artefacts. By subtracting EOG signal from the contaminated EEG signal we can obtain the true EEG signal. A constant K is introduced to specify the amount of EOG signal to be subtracted. One of the most popular techniques of estimating the value of K is linear regression (Croft et al., 2005). The different types of K can be estimated for different types of EOG (Gratton, 1998) artefacts and different frequencies of EOG artefacts (Gasser et al., 1985). One of the main disadvantages of this method is the fact that EOG signal is also contaminated by EEG signal, therefore using this method will always result in removing part of genuine EEG signal.

Blind Signal Separation

In artefact removal, Blind Signal Separation (BSS) identifies the components that are attributed to artefacts. This part of the signal is removed and the signal is reconstruct without these components. Two important techniques of BBS are used in BCI: Independent Component Analysis (ICA) and Principal Component Analysis (PCA). These methods are also used in feature extraction and are described below. ICA has been successfully used to remove ocular artefacts in BCI by Jung et al. (2001) and Vigário et al. (2000). De Clercq et al. (2006) have used ICA to remove muscle artefacts. PCA has been used by Lagerlund et al. (1997) to remove ocular artefacts. The main advantage of BBS techniques is the fact that they do not require any EOG information to perform artefact rejection, however visual inspection is often required to identify the artefact components. The main disadvantage of the BBS methods is the requirement of independence of the artefacts from the signal of interest. This requirement is especially important in case of PCA and it cannot always be met, as the eye and muscle movement are often strongly correlated with the performed task and therefore with the EEG signal.

Instead of avoiding, rejecting or removing signal artefacts some human-computer interface (HCI) systems acquire artefacts and process them to provide the communication path. An example of this kind of system that allows users to control a spelling program and web browser was proposed by Królak and Strumiłło (2009). Some systems combine BCI technology with artefact processing. This kind of systems provide good reliability, often greater than BCI systems, they cannot however be classified as BCI, as the communication between the man and the machine involves the use of muscles. Moreover, these systems cannot be used by severely disabled people for whom the control of voluntary movements is impaired.

2.7 Feature Extraction

BCI tries to classify patterns in brain signal according to its features. In order to successfully classify signal patterns appropriate features that distinguish the patterns have to be extracted. Feature extraction algorithms attempt to find the features best capture the similarities within the class and differences between the classes. The fact that brain signals are very noisy and the signal of interest may be overlapped by signals generated by other brain activities that are not related to the performed task as well as signals generated by muscles and external noise (e.g. electrical noise) makes this task very challenging. The techniques used for feature extraction can be categorised into a number of distinctive groups: dimensionality reduction, time frequency algorithms and common spatial pattern algorithm.

2.7.1 Dimensionality Reduction

In BCI systems, especially those EEG based feature vectors are often of high dimensionality. EEG samples from multiple channels are usually concatenated to form feature vectors. Dimensionality reduction attempts to limit the size of the feature vector to make classification more robust and less computationally demanding.

Principal Component Analysis

Principal Component Analysis is a statistical procedure that transforms (using orthogonal transformation) a set of observations (some of which may be correlated) into uncorrelated variables called principle components. The number of principle components may be lower or equal to the number of original variables. The first component accounts for the largest amount of variance in the data. Every next component accounts for lower chunk of variance. If lower number of components than the number of original variable explains all the variance then the number of principle components will be smaller than the number of original variables. In practice, the components that explain very small amount of variance may be excluded as insignificant and the dimensionality of data is reduced.

PCA does not guaranty the most optimal dimensionality reduction as the produced components may not contain the features that best distinguish between the classes, however it has been proven to be a reliable method of noise reduction.

Independent Component Analysis

As we have already said, signals collected on the top of the scalp are a mixture of signals from different sources (multiple cognitive activities and artefacts). Independent Component Analysis tries to separate the components of the initial signal. The assumptions required by ICA are that the components of the signal are non-gaussian and independent. ICA can be used for pre-processing (e.g. removal of ocular artefacts) (Gao et al., 2010), however artefacts are not always independent of the neural activity that we try to classify. In this case removal of artefacts can lead to the removal of components that would be good features for classification.

2.7.2 Time-frequency Algorithms

Time-frequency algorithms attempt to transform the signal from time to frequency domain. The most often used type of time frequency algorithm is Fourier transform (for explanation see Sanei and Chambers

(2008)). This algorithm is sometimes used in BCI to provide a simple measure of participant's state.

Wavelet Transform

Fourier Transform provides information about the frequency content of the signal; it does not however provide information about the temporal position of this frequency content and this information is very important for feature extraction. To solve this problem a short term Fourier transform (STFT) was proposed. The STFT partitions signal into small time windows and applies FT to these time windows. This method creates a trade-off between the temporal and frequency resolution. The shorter the time window the higher the temporal resolution and the lower the frequency resolution, and vice versa. To overcome this limitation, wavelet transform (WT) uses mother function that is applied to a modulated window that is shifted at various scales. This allows WT to provide good spatial and temporal resolution. WT has been successfully used to extract features in P300, ERP and SCP based BCI systems (Bostanov, 2004; Senkowski and Herrmann, 2002; Mason and Birch, 2000). One of the drawbacks of WT is the fact that the success of this method relies on the appropriate choice of the mother function.

Matched Filtering

In Matched Filtering a known signal (template) is correlated with an unknown signal to detect the presence of known signal in the unknown signal. In EEG-based BCI the EEG signal is correlated with a number of templates, where each template represents different intention of the user. The higher correlation implies better matching between the signal and the user's intention.

2.7.3 Common Special Pattern

In Common Special Pattern (CSP) the EEG signal is projected into a subspace where the similarities between classes are minimised and differences are maximised. This data transformation creates output data with the optimal variance for subsequent classification. CSP has been shown to be effective for data motor imagery based BCI (Wang et al., 2006).

2.7.4 Genetic Algorithm

Genetic algorithm (GA) belongs to the larger class of evolutionary algorithms. It is an optimization procedure that mimics the process of natural selection. GA generates solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. In the field of BCI, GA has been used as a feature extraction method (Dal Seno et al., 2008). In GA, the optimal solution is obtained by an evolution of a population of candidate solutions (called individuals, creatures or phenotypes). Each candidate solution possesses a set of properties (called chromosomes or genotype) which are encoded as strings of binary or non-binary information. These strings can be mutated or altered. Different types of GAs are used. A simple GA is presented here.

GA starts with a number of randomly generated candidate solutions, the initial population. If information regarding the previous final solutions is available, the initial population can be directed towards the areas where optimal solutions are more likely to be found using smaller number of iterations. The fitness of each of the candidates in the population is evaluated and some of them (those with lower fitness) are discarded to create space for newly generated individuals. Others can be selected as parents to create the next generation. New individuals are created by crossover operation. In this step, chromosomes of previously selected parents are fragmented and combined to create a new offspring. To keep the population size stable, the number of offsprings is usually the same as the number of discarded candidates from the previous generation. After the crossover step, mutations are introduced to avoid being trapped in local sub-optimum and explore the entire search space. The algorithm is terminated when one of the criteria is met: (1) solution is found that satisfies minimum fitness, (2) predetermined number of generations is reached, (3) allocated time is reached or (4) the results have reached a plateau – each successive iteration no longer produces better results.

2.8 Classification

BCI systems employee machine learning algorithms for classification of neurological signals. Two different approaches in machine learning include regression and classification. Regression is mostly used to predict a continuous value of a parameter (e.g. price of a house given area, number of rooms and age of the house) and is of little use in BCI. Classification allows assigning a sample value into a number of discrete classes (e.g. reaction to target or non-target letter in BCI speller). Two types of classification can be distinguished: supervised and unsupervised. In case of unsupervised classification the training data does not contain labels (information regarding the class to which each sample belongs). The procedure attempts to find the classes in the data and then assign the test samples to the classes created. In supervised learning the label is provided. Supervised classification is the method most often used in BCI. The most popular classification algorithms are discussed below.

2.8.1 Artificial Neural Networks

Artificial Neural Networks (ANN) are, together with linear classifiers, one on the most often used machine learning methods. ANN were inspired by the structure and the functionality of brain cortex (see section 2.4) and are a simplified representation of the cortex. Artificial neural network is a system of neurons which are interconnected.

A typical ANN used in BCI is a Multilayer Perceptron (MLP), which is composed of a several layers of neurons (see Figure 2.4). The number of hidden layers may be higher than one. Each neuron connects to the neurons of the previous layer and the output neurons determine the class of the input feature vector (Bishop et al., 1995).

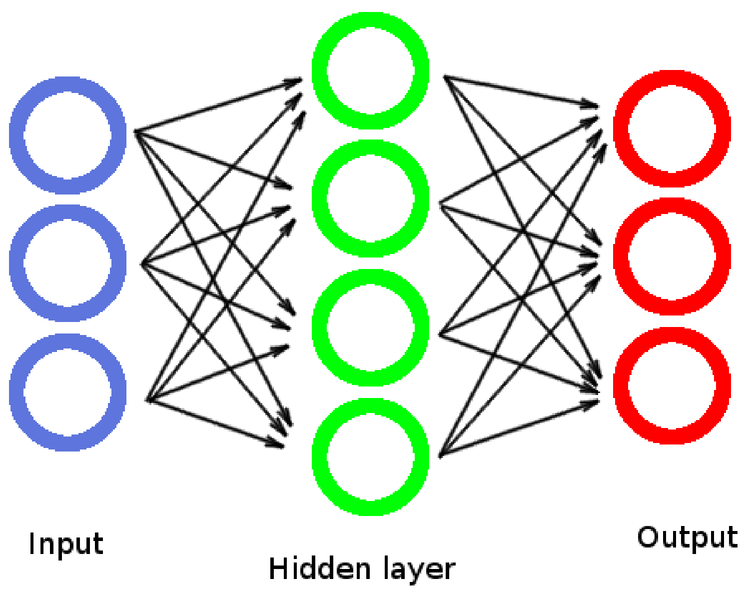

Figure 2.4: Visual representation of neural networks. Circles represent neurons organised in three layers and arrows represent connections.

2.8.2 k-Nearest Neighbours Classifier

k-Nearest Neighbours Classifier is based on the assumption that members of different classes create clusters in the feature space; which means that if we plot samples belonging to different classes in n-dimensional space (where n is the number of features taken into account - length of the feature vector) the samples of different classes will form distinctive clusters. Measuring the metric distance between the sample to be classified (test feature vector) and k nearest neighbours (samples lying closest to the test sample), taking into account the class to the neighbours allows to class the test sample as a member of one of the classes. In a very simple example, the test sample is included into the class from which the higher number of nearest neighbours comes. k-Nearest Neighbours Classifier is proven to be effective in low-dimensional vectors; therefore its use in BCI is limited. It has, however been successfully used in MI-based BCI with multiple classes (Schlögl et al., 2005; Kayikcioglu and Aydemir, 2010).

2.8.3 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is by far the most popular classification algorithm used for BCI. LDA provides relatively good classification accuracy with relatively low computational complexity. LDA is therefore ideal for BCI systems that require fast response with low computational power. LDA assumes that the classes are linearly separable by a hyperplane (for two classes) or a number of hyperplanes (for more than two classes) in the feature space. The class, to which the test sample belongs, depends on which side of the hyperplane it is found (see Figure 2.5). A number of BCI systems used LDA for signal classification (Blumberg et al., 2007).

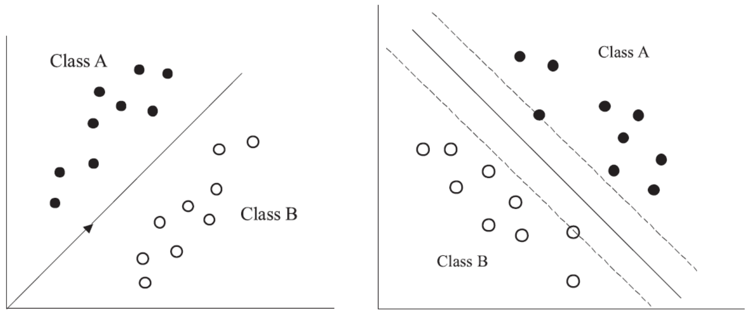

Figure 2.5: On the left, visual representation of LDA. On the right, visual representation of SVM. Both for two-class problem.

2.8.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) classifiers are similar to LDA classifiers. Similarly to LDA, SVM constructs a hyperplane or a set of hyperplanes and separate the feature vectors into several classes. However, SVM introduces margins which are the distance between the hyperplane and the nearest training samples (see Figure 2.5). The position of the hyperplane is selected to maximise the margins.

2.8.5 Combining classifiers

Most BCI systems use a single classifier for classification. However, recently systems that combine a number of classifiers have been proposed. A combination of classifiers is likely to provide better classification accuracy than one classifier. The following combination strategies can be used.

Boosting

In boosting a number of classifiers perform classification in cascade. Each classifier focuses on the errors of the previous one. Boosting can result in a very strong classifier based on several weak ones and it is very unlikely to over-train. It is however very sensitive to mislabelling of data. Boosting has been applied in BCI (Boostani and Moradi, 2004).

Voting

In algorithms using voting, a number of classifiers are used. Each of the classifiers classifies the input feature vector and the final class of the feature vector is the one which was selected by the majority of the classifiers. Voting is the simplest and most popular way of combining classifiers (Rakotomamonjy and Guigue, 2008; Qin et al., 2005).

Stacking

In case of stacking more than one "layer" of classifiers is used. The output of a set of primary classifiers (level-0) is feed to a meta-classifier (level-1) which performs the final classification (Lee and Choi, 2003).

2.9 BCI Applications

Different applications have been proposed for BCI. Historically the researchers had been concentrated on clinical aspects of BCI such as communication, motor restoration, neurorehabilitation, environmental control and locomotion. Recently, however the interests are shifting towards entertainment. Each of the mentioned applications is shortly described below.

2.9.1 Communication

As communication is an essential human activity, it has always been one the main areas for BCI application. BCI technology provides the ability to communicate for severely disabled people, who are otherwise not able to do it. This kind of application, together with motor restoration is the most pressing area of research in BCI. A number of approaches have been used and they use different BCI paradigms. What is common in all of the approaches is the fact that most of them use a display of a keyboard on the screen and the user selects the letter from the alphabet by the means of BCI. These devices are often called spellers. Hinterberger et al. (2004) used slow cortical potentials (SCPs) for letter selection. SCP requires extensive training. However, paralysed users were able to move a cursor on the screen by altering their SCP.

The most popular BCI paradigm used for spellers is P300 paradigm. The main advantage of this paradigm is the fact that P300 response is spontaneous and does not require long training. Many systems of this kind have been developed using different types of classifiers and displays. To choose an appropriate letter (out of 26 in English alphabet) each of the 26 letters has to be illuminated at least once. This is very time consuming and the researchers try to minimise the time required for letter selection by proposing different displays.

Townsend (Farwell and Donchin, 1988) developed a speller in which the letters are illuminated in rows and columns. Their system contained 36 symbols displayed in a 6 x 6 array. Rows and columns were randomly illuminated (twelve illuminations in total). Each symbol was illuminated twice - once in a row and once in a column. The identification of the correct row and correct column allows finding the symbol on which the users concentrated. Fazel-Rezai and Abhari (2009) proposed a two stage approach to a BCI speller. The selection of the letter is performed in two stages. Firstly, letters are organised in groups that are presented together in different regions of the screen and flash together. In the first stage, the user chooses one of the groups and then only the letters from this group are displayed. Recently, predictive dictionaries, well known from mobile phones, have been adapted for BCI spellers (Ron-Angevin and da Silva-Sauer, 2013). Predicted words are displayed on the screen and the user can concentrate on one of these words instead of "typing them to the end".

Other devices relying on BCI artefacts, like eye blinks, have been proposed. These systems, however, cannot be classified as BCI, because eye blinks engage muscles and the communication between the brain and the machine is indirect.

2.9.2 Motor Restoration

Many neurological conditions such as spinal cord injury (SCI), multiple sclerosis (MS) or stroke can destroy sensory and motor functions dramatically decreasing people's quality of life. BCI can provide help for those people by restoring their motor functions. Two approaches can be identified.

Functional electrical stimulation (FES) can be used if the functions of some peripheral nerves and muscles are intact. Peripheral nerves are depolarised by electrical currents which leads to contraction of muscles. EEG-based BCI can be used to create commands that control the FES. Based on these technologies, Pfurtscheller et al. (2003a) created a system that allows users to grasp a cylinder with paralysed hand. For patients with more severe motor disabilities neuroprostheses can be used. In this case, the signals provided by EEG (or ECoG) are translated into command that move a prostatic device, usually a prostatic hand. Pfurtscheller et al. (2000) showed that Rolandic oscillations produced by motor imagery could be used to control a hand orthosis in tetraplegic patient with spinal cord injury, however long training was required.

A different approach was proposed by Müller-Putz et al. (2005), who used SSVEP-based BCI to control the prostatic limb. The user could concentrate on one of flickering light build into the prostatic device and depending which light the user concentrates on, different command would be send to the device.

2.9.3 Neurorehabilitation

The studies described in section 2.9.2 provide an alternative for normal motor functions using prostatic or orthotic devices. BCI can also be used to restore natural motor functions in people who suffered stroke. In this case, a BCI system is used as neurofeedback device that allows for restoration of the functions in the brain areas damaged by stroke relying on the phenomenon of brain plasticity.

In a study of clinical population, Ang et al. (2010) showed that stroke patients could control BCI based on motor imagery and a four week training led to significant improvement in motor control. Systems using MEG-based BCI technology have also been successfully used for rehabilitation of stroke patients. As describer in section 2.3.4, MEG provides better spatial resolution which allows for more precise targeting of the damaged brain area. Caria et al. (2011) used a combination of EEG and MEG BCI training to restore lost motor functions in a post-stroke patient, and using fMRI and diffusion tensor imaging showed changes in the brain structures associated with motor control.

2.9.4 Environmental Control

One of the main goals of BCI is to promote the independence of people with severe mobility problems and decrease their reliance on carers and social support systems. People with mobility and motor difficulties are often housebound and moving inside the house as well as controlling household appliances poses difficulties. BCI can help in solving these problems.

Large number of systems have been developed that attempt to provide environmental control for the users. Most of these systems rely on EEG recording. Gao et al. (2003) developed a system that controlled video tape recorder, television set and air conditioning using SSVEP-BCI. The main advantage of this system was the small amount of training required.

A system developed by Cincotti et al. (2008) allows users with varying disabilities of motor functions to control domestic appliances (lights, TV and stereo sets, a motorized bed, an acoustic alarm, a front door opener, and a telephone, as well as wireless cameras to monitor the surrounding environment). A combination of traditional inputs (keyboard, joystick), head tracking and sensorimotor based BCI is used to control the system. fNIRS-BCI has also been proposed for this pur-

pose. A study by Ayaz et al. (2011) showed that 84 per cent of users (healthy participants) of fNIRS-BCI were able to use it to engage with object in virtual environment. Participants were required to navigate a maze using computer keyboard, however to enter and exit the maze they had to open virtual door and this could only be done by interacting through fNIRS-BCI protocol. This study does not present the use of fNIRS-BCI in real home environment; it does however show that application of fNIRS-BCI in home environment is feasible.
Invasive techniques have been shown to be very promising for this type of applications. Tetraplegic user with sensors implanted in primary motor cortex was able to control devices such as television, as well as email application, while conversing (Hochberg et al., 2006).

2.9.5 Locomotion

A very important aspect of independence is the ability to move freely, something healthy people take for granted. Application of BCI technology enables users with severe motor disabilities to control wheelchair. This is however a difficult task as the low rate of information transfer makes a continuous and fluid control of a wheelchair challenging. However, a number of studies using different BCI paradigms often coupled with other technologies show that this goal is in fact feasible. Tanaka et al. (2005) developed a BCI controlled wheelchair based on motor imagery. The limitation of this approach was that the wheelchair could move only between specified positions on the floor. This idea was refined by Carlson and Millán (2013) who combined motor imagery BCI with computer vision/obstacle detection and motion planning to create a truly intelligent BCI wheelchair, which can successfully navigate in changing environment. Preliminary studies showed that four healthy users could master the use of this wheelchair. Iturrate et al. (2009) applied P300 paradigm to this problem. In their system the user is presented with a simplified surrounding displayed on the screen in front of him. A number of flickering stimuli is overlaid on the display. By concentrating on one of the stimuli the user chooses the area to which to move the wheelchair. This machine was also able to avoid collisions with obstacles in the environment detected by a laser scanner.

2.9.6 Entertainment

The main focus of the BCI field has been on creating application for disabled users. Improvement in the technology and the advent of relatively cheap and portable devices like Emotive Epoch (Emotiv EEG Neuroheadset) and NeuroSky MindWave (NeuroSky MindWave), available to the wider public, opened the possibility for independent programmers to create entertainment applications and the use of BCI as an input device for computer games. Researchers also explore these possibilities.

Simple games such as pong and pacman have been adopted to use BCI. Marshall et al. (2013) and Bordoloi et al. (2012) created pacman games in which a user could navigate a maze using motor imagery. A pong game relying on simple biofeedback (Moyes and Jiang, n.d.). Different variants of the tetris game have presented by Pires et al. relying on P300 and motor imagery BCI. BCI technology was applied to a well know computer game World of Warcraft by van de Laar et al. (2013). They used the power of alpha band over parietal regions, which is believed to be linked to relaxation. By controlling the alpha band the user could change the controlled avatar from a bear - for a state of low relaxation to a druid - for a state of high relaxation. The abilities of the avatars in the game correspond to the state indicated by the measured alpha frequency in EEG signal. Relaxed user controlled a druid that requires intelligence and mental concentration and a user in the state of "stress or agitation" controlled a bear (for review of BCI technology in computer games see Marshall et al. (2013).).

2.9.7 Other and Potential Applications

The imagination of engineers and developers has no limits. Some of their creations include: BCI-controlled cat ears that show the user's mood (Show your mood with brain-controlled "NECOMIMI" cat ears) as well as a mind controlled flame thrower (The joy of mind-controlled flamethrowers). BCI has also been applied in neuromarketing; one of rapidly growing areas of market research. A number of companies offering this kind of services can be found online (NeuroFocus; Neuro Insight). Using direct information about the neural activity of the users can provide an inside to costumer behaviour not possible to obtain by conventional market research.

With further improvement of BCI technology new and exciting applications can be imagined. BCI systems that monitor users' attention level while steering a car, a train or a plane would greatly improve the safety of transport. At this point in time, the amount of electrical noise in these environments make this applications infeasible, however with further improvement in artefact removal they may someday become part of our everyday lives.

2.10 BCI Illiteracy

BCI provides alternative means of communication for people with motor impairments as well as tools for rehabilitation and entertainment, but not everyone can benefit from these advantages of BCI technology. For each paradigm there is a group of people, around 20 per cent, that are not able to successfully communicate through BCI (Tan and Nijholt, 2010). This problem may be caused by a number of reasons. Some users may not be able to use a certain paradigm due to the individual variations in their brain structures.

All healthy brains have the same structures in roughly the same places, however some cortical areas may not produce EEG signal detectable on the scalp. For example, this may result from the folding of the brain. If the area of interest is placed deep in the brain sulcus the activity generated by this area may be difficult to detect on the surface of the scalp. Some users may also produce very strong muscle artefacts that may decrease signal-to-noise ratio in the recorded EEG and make the classification of the signal difficult. This may be observed in patients with cerebral palsy (CP), a developmental condition which symptoms include spasticities, spasms and other involuntary movements (e.g. facial gestures) as well as unsteady gait and problems with balance (Rosenbaum et al., 2007). Patients with very severe CP may be unable to walk or speak and would greatly benefit from the development of suitable BCI technology.

BCI performance may also be affected by other psychological and cognitive factors. These factors, as well as the mechanisms determining performance and illiteracy in three of the most popular BCI paradigms are described below.

2.10.1 Illiteracy in SMR-based BCI

EEG equipment can detect sensorimotor, such as mu (7–13 Hz) and beta (13–30 Hz) frequency bands (Pfurtscheller and Lopes da Silva, 1999). These rhythms are strongly associated with motor action. The amplitude of sensorimotor rhythms changes when neural activity related to motor action is performed, although the actual movement is not necessary (Jeannerod, 1995; Pfurtscheller et al., 1997) and imagery of motor action produces sensorimotor rhythms similar to the ones produced by movement (Jeannerod, 1995). Moreover, users can learn to control the modulation of sensorimotor rhythms, making this brain signal a prime candidate for use with BCI systems (Pfurtscheller and Neuper, 2001; Blankertz et al., 2010).

Sensorimotor rhythms manifest as two types of amplitude modulations: They either appear and their amplitude is enhanced, known as event-related synchronization (ERS), or disappear and their amplitude is reduced, called event-related desynchronisation (ERD) (Pfurtscheller and Neuper, 2001). ERD can be observed in the mu band (where it starts 2.5 s before the onset of the movement, reaches maximum shortly after the onset of the movement and recovers to the baseline level within a few seconds) and in the beta band (a short ERD can be observed during movement initiation followed by ERS that reaches its peak after movement execution. This ERS in beta band occurs while the ERS is still observable in mu rhythm. Another rhythm that can be related to movement execution and imagery is gamma rhythm (36-40 Hz). Gamma ERS can be observed shortly before the movement onset.

Communication using ERD-based BCI systems is possible if the user can reliably produce activation that result in different EEG patterns associated with different movements (Neuper et al., 2005). Voluntary modulation of sensorimotor rhythms through motor imagery is possible, it is, however not easy. It is important to concentrate on first person, kinaesthetic imagery as the third person visual imagery provides activation patterns much different than the ones produced by real movement.

It has been found that proficient ERD-based BCI users engaged significantly larger cortical area (measured by fMRI) during motor imagery and motor observation (Halder et al., 2011) as compared to illiterate users. This difference was not observed during motor execution. Dickhaus et al. (2009) found the performance on SMR-based BCI can be predicted by power spectral density (PSD) measured during two-minute period of resting state over left and right motor cortex. Research by Hammer et al. (2012) showed that visuo-motor coordination and the ability to concentrate on the task correlated positively with performance. Kinaesthetic motor imagery has also been found to be predictive of SMR-based BCI performance.

Training systems for sensorimotor modulation have been developed. Some provide visual or auditory feedback (Nijboer et al., 2008), other allow trainees to observe their cortical activity on-line (Hwang et al., 2009). Many of the best known BCI systems: Wadsworth (Wolpaw et al., 2000), Berlin (Blankertz et al., 2008) or Graz (Pfurtscheller et al., 2003b) employ sensorimotor rhythms as the control signal.

2.10.2 Illiteracy in P300-based BCI

The repetition of events and the recording and averaging of the evoked, time-locked neural signal yields what is known as an event-related potential, which contains characteristic peaks that have amplitudes and latencies, and which can be used to somewhat disambiguate the signal from the noise in the EEG data. Peaks are called components when they are reproducible and named after their amplitude and latency.
The P300 (also called P3) wave is a component of an event related potential (ERP) which is elicited by infrequent auditory, visual or somatosensory stimuli. P300 is a positive peak in EEG signal occurring 300 msec after onset of the event, normally elicited using the oddball paradigm, as a response a low probability stimulus that appears amongst high probability stimuli (Farwell and Donchin, 1988; Donchin and Smith, 1970). P300 is also augmented when one perceives a stimulus that is regarded to be important; a stimulus one pays attention to (Gray et al., 2004).
In P300-besed BCI systems, the classifier tries to identify which flash elicited a robust P300. In order to successfully encode user's intentions the attended stimuli has to produce a P300 that is different from the P300 produced by non-attended targets. A small P300 that is not very different from the EEG signal elicited by non-target stimuli will

result in poor BCI performance. According to Polich (1986) and Conroy and Polich (2007) ten per cent of participants do not produce P300 components and these subjects may have difficulty using P300-based BCI.

2.10.3 Illiteracy in SSVEP-based BCI

Steady state visually evoked potentials (SSVEP) are electrical signals in the brain elicited in response to visual stimuli of a specific frequency (between 3,5 Hz and 7 Hz) (Beverina et al., 2003). SSVEP produced by a repeated flash stimulation shows a sinusoidal-like waveform of frequency the same as (or the multiple of) the frequency of the stimulus. In typical, SSVEP BCI the users can communicate with the machine by concentrating his eyes on a flashing target on the screen (Zhang et al., 2010). The acquired EEG signal is transformed into frequency domain. A spike can be detected for the frequency of the stimulus or a multiple of that frequency (Allison et al., 2008). If the spike is large it can be easily distinguish from the background noise. A small spike, difficult to detect, may result in poor BCI performance.

2.11 Attention

Attention is a cognitive process that involves selective concentration on one object or thought while ignoring other stimuli. It can also be understood as the allocation of cognitive resources (Anderson, 2009, p. 64). This definition captures the essence of attention, but it does not, however, fully explain the diversity of cognitive processes involved in this multifaceted cognitive ability.

Corbetta and Shulman Corbetta and Shulman (2002) proposed a model of attention with two constituent parts, where two top-down and bottom-up systems are proposed.

The top-down system is involved in voluntary orienting and its activity increases when one is presented with cues indicating where or when to direct attention.

The bottom-up system is an involuntary attention system that increases activity when abrupt changes in sensory stimuli take place.

Another model of clinical origin was proposed by Sohlberg and Mateer (1989). The model was based on the clinical experience with brain damage patients and distinguishes five levels of attention:

1. Focused attention which is understood as the ability to respond to visual, auditory of tactile stimuli.

2. Sustained attention describes ability to continuously respond while performing a repetitive task.

3. Selective attention also called "freedom from distractibility" is understood as the ability to maintain a behavioural or cognitive task despite competing destructions.
4. Alternating attention is a type of mental flexibility that allows people to shift their focus of attention between tasks with different cognitive requirements.
5. Divided attention is the ability to respond simultaneously to multiple tasks or multiple task demands.

These five levels of attention are presented in hierarchical order. This is also the order of attention recovery after brain damage.

Posner proposed (Posner and Petersen, 1990; Posner and Boies, 1971) tripartite model of attention. This model comprises three functionally distinctive networks that are responsible for performing the operations of alerting, orienting, and conflict monitoring (executive attention).

Alerting is a faculty that allows one to stay vigilant towards the surrounding, orienting is responsible for directing attention towards appearing stimulus and conflict monitoring is used when there is a conflict between competing tasks and responses. This model has been validated using behavioural and neuroimaging studies. The neurological components of all three attentional systems are presented in Figure 2.6.

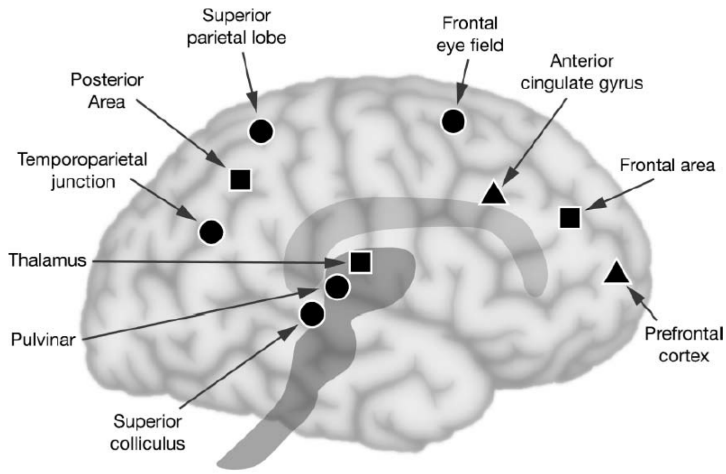

Figure 2.6: Neurological components of three attentional networks: squares - alerting, circles - orienting, triangles - executive attention. Adapted from (Posner and Rothbart, 2007).

Posner also developed a task that allow to measure attention across the three proposed dimensions (see section 4.6.2).

2.12 Dysfunctions of Attention

Attention plays an important role in many areas of life. People with attention disorders such as attention deficit hyperactivity disorder (ADHD)or attention deficit disorder (ADD) (Association, 2000), which is regarded to be one of the most common psychiatric disorder amongst children (Kooij et al., 2010), experience lower quality of life (Danckaerts et al., 2010). ADHD is also associated with increased health cost for the people and their families, disruption in professional and personal life as well as lower earning and increased crime rate (Smith, 2009). In light of these facts finding an efficient ADHD therapy becomes an important social and economic challenge.

2.13 Meditation

Meditation has been a subject of research since 1970s (Wallace, 1970), however no single definition of meditation has yet emerged. The lack of a single definition may be dictated by the fact that the word meditation describes different practices that originated in different spiritual traditions. Lutz et al. (2008) grouped meditation into two categories: focus attention and open monitoring.

1. Focus attention involves sustaining attention of an object (e.g. sensations caused by breathing). To keep the concentration on the chosen objects the meditator has to constantly monitor the quality of attention. Practicing FA meditation trains three skills involved in the attention regulation. The first is the ability to monitor distractions without destabilising the focus on chosen objects. The second is the ability to promptly disengage from the distraction and the last one is the faculty that allows to promptly return the attentional focus to the chosen object.

2. Open monitoring, also called mindfulness, involves non-reactive monitoring of the content of experience from moment to moment. Focus attention meditation is often used as an initial stage to

calm the mind and deal with distractions. When this is obtained, one tries to remain in the monitoring state while being attentive to everything that occurs in one's mind without focusing on any explicit object.

Meditation has been reported to produce beneficial effects in many aspects of life, from stress reduction (Reibel et al., 2001; Nidich et al., 2009), through health related behaviour (Haaga et al., 2011) to cognition (Biegler et al., 2009) and overall improvement in quality of life (Reibel et al., 2001).

Effects of meditation can be observed in structural changes of the brain and changes in EEG signal. Practice of meditation results in increased cortical thickness in regions associated with attention, interoception and sensory processing (Lazar et al., 2005; Grant et al., 2012).

2.13.1 Meditation as Training of Attention

A number of studies have shown the effects of meditation on cognitive functions such as short term memory and attention. MacLean et al. (2010) showed that intensive meditation improves sustained attention. Results obtained by Tang et al. (2007) showed that even short (5–day) meditation training can bring improvements in attention.

Jha et al. (2007) speculate that focused attention meditation results in changes to dorsal (voluntary) system and open monitoring changes ventral (involuntary) attention system.

2.13.2 Attention, Meditation and BCI Illiteracy

A number of articles describe the use of BCI for attention training. For instance, Jiang et al. (2011) developed a three-dimensional computer game which allows users to control the game by focussing attention on particular stimuli on the display. The aim of this game is to train attention and combat the symptom of attention deficit hyperactivity disorder (ADHD). A similar system was developed by Lim et al. (2012). The researchers investigated the BCI-based attention training game system on unmedicated ADHD children and obtained significant improvement after 8 weeks of training.

Meditation has also been linked to BCI performance. Lo et al. (2004) reported that mind attentiveness focus during the beginning stage of Zen meditation allows meditators to better control their EEG signal and improves the proficiency in event-related desynchronisation based BCI. They suggest that meditation might be used as training for BCI. Similarly, regular practice of meditation has been shown to be related to improved classification accuracy. In a study by Eskandari and Erfanian (2008) meditation practitioners achieved better classification accuracy than the control group. Mindfulness meditation was also investigated with respect to P300-based BCI (Lakey et al., 2011). Subjects who engaged in mindfulness meditation induction before BCI task were significantly more accurate than the control subjects.

2.13.3 Conclusion

Research into BCI illiteracy has concentrated mostly on demographic factors of this phenomenon (see section 2.10). The researchers have not yet investigated the psychological determinates of BCI performance. The research cited in section 2.13.2 indicates the existence of such relation. The two experiments presented in this thesis investigate the relation between attention and BCI performance.

Chapter 3

Experiment 1

3.1 Introduction

This chapter presents the results of an experiment investigating the use of an off-the shelf BCI system to induce a state of relaxation, much like a meditative state. The system uses grid based road network generator as the visual feedback. The road network displayed on the screen changes depending on input collected from the Emotiv Epoch device. The road network generator was used to build on the previous research described in Appendix G. To stay as close as possible to what BCI is "in the real world", we decided to use Emotiv Epoch device, as it is one of the off-the-shelf systems most used in the BCI community (Nicolas-Alonso and Gomez-Gil, 2012).

We compared three following conditions (independent variable): (1) grid - participants were asked to relax while observing a grid based road network described in section 3.3.2. Feedback was provided to par-

ticipants where more symmetrical display corresponded with higher level of relaxation, (2) video - participants were asked to relax while watching a video, (3) eyes closed - participants were asked to relax with their eyes closed. Grid was the experimental condition and video and eyes closed were the control conditions. On-line feedback was provided using emotive affective suite and the measure of meditation was used (for more information see section 3.3.2). EEG signal was also collected for further off-line analysis as well as information regarding the subjective user experience (dependent variables) were collected and analysed.
We hypothesised that the use of on-line feedback would lead to higher level of relaxation measured by EEG and users' ratings.

3.2 Participants

Eight participants took part in the experiment. The group consisted of 3 males and 5 females. All participants had correct or corrected to normal vision and no neurological disorders which could affect the use of BCI.

3.3 Experimental Setup

3.3.1 Hardware

The hardware components of the proposed system include the Emotiv Epoch neuro-headset and a laptop PC. The headset is equipped with 14 wet electrodes and 2 references. The electrodes are placed on the international 10-20 system (Niedermeyer and da Silva, 2005), an internationally recognized method of electrode placement for EEG testing. The headset provided pre-processed EEG and gyroscope data that we subsequently processed using Emotiv SDK EmoEngine.

3.3.2 Software

The software side of our BCI system was developed using the Emotiv Development Kit and written in the C++ programing language, spanning interfaces to the Emotiv Epoc headset (Emotiv EEG Neuroheadset) and a display using OpenGL (OpenGL). The stimuli used in this project were a simple representation of a grid based road network (see section 3.3.2). In the proposed experiments the participants could manipulate two of the display parameters through the BCI system: a) the amount of vertex displacement and b) the number of roads added or deleted. The program continuously queried the EmoEngine (Emotive Software Development Kit) for access to the EEG data, through several variables categorised in the following three groups.

1. Affective - allows to monitor the user's emotional state in real time and includes the following parameters: short and long term excitement, engagement/boredom, frustration and meditation. According to Emotive Software Development Kit User Manual (Emotive Software Development Kit User Manual), engagement is understood as the experience of alertness and conscious direction of attention towards task related stimuli and is characterised by increased psychological arousal, increased beta waves and attenuated alpha waves, while excitement is experienced as an awareness or feeling of psychological arousal with a positive value. It is characterised by an activation of sympathetic nervous system that manifests in a range of psychophysical responses e.g. pupil dilation, eye widening, sweat etc. Emotive documentation does not provide any explanation of mediation and frustration. However according to (Vaitl et al., 2005) meditation is normally used to describe practises of engaging a specific attentional set that affects mental event and helps controlling the body and the mind. The state of meditation is normally associated with the increase in alpha and theta band power (Andresen, 2000). Emotional stress (frustration) is often associated with hemispheric asymmetry. The alpha band power in the right hemisphere is increased under stress conditions (Coan and Allen, 2004). It is, however unknown whether these EEG correlates are used by emotive engine

to calculate the measures of meditation and frustration.

2. Expressive - the signal measured by the headset is used to interpret user's facial expressions e.g., smile, eye blink.

3. Cognitive - interprets a user's conscious thoughts and intents. The use of these measures requires training in which the user chooses a mental operation (e.g., motor imagery of moving the right arm) and this operation is associated with an operation in the virtual environment (e.g. moving to the right).

The cognitive parameters are intended to control object in virtual environment or the real world, however each of these parameters can be used for that purpose.

Road network generator

The road network generation algorithm [1] (see Appendix G), features were chosen empirically, based on a visual inspection of grid-like cities using Google Maps (Google Maps). The network is generated in a number of stages. First, a basic grid is generated that includes vertices as well as tertiary horizontal and vertical roads joining each vertex to its neighbours. At this stage the number of cells is entered as parameters to the generator. In the second stage, a number of streets

[1] We developed the road network generator in the first part of this thesis work, and we chose to use it for performance feedback because it permits the visual representation of orthogonal dimensions. This part of the work is described in O' Connor, S., Fialek, S., Roesch, E. B. and Peters, C. (2012). Towards Procedurally Generated Perceptually Plausible Inhabited Virtual Cities: A Psychophysical Investigation, Proceedings of Intelligent Agents in Urban Simulations and Smart Cities Workshop, ECAI 2012, Montpellier, France.

(collection of roads joined together) are removed. Primary and secondary streets are then introduced. Two final parameters which will be controlled by the user are: vertex displacement and number of roads deleted. An example of the effects of alteration of the parameter vertex displacement is shown in Figure 3.1. Participants were presented with the changes in the display, reflecting their "neural state" as registered by the Emotiv kit, in real time.

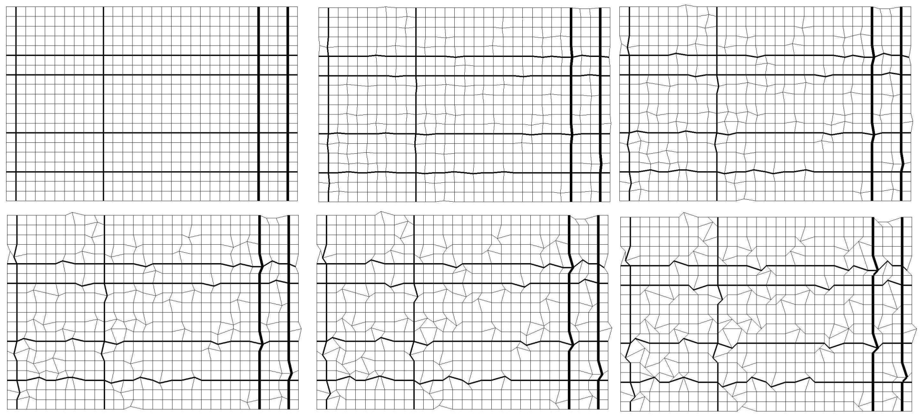

Figure 3.1: Example outputs of the grid based road network generation algorithm with different values of vertex displacement parameter (from 0.0 in the top left to 1.0 in bottom right).

Similar Emotive applications using affective measures have been developed and these include Mindala (Mindala), in which users can train their meditation skills by controlling a mandala and Spirit Mountain (Spirit Mountain Demo Game) (demo version available at the moment) in which users have to show control of affective parameters (excitement) to complete tasks in the game.

3.4 Experimental procedure

Before the experiment Emotiv Epoc headset was applied and calibrated using Emotiv Control Panel (Emotive Software Development Kit User Manual) to ensure the good connectivity and quality of signal. During the experiment participants were seated in front of the computer and instructed to relax why performing all three conditions. To avoid the learning and fatigue effects the conditions were performed in random order. After each condition the participants were asked to rate level of relaxation on the scale form one to ten.

3.5 Data analysis

EEG data were pre-processed and analysed using custom scripts utilising the MatLab EEGLAB toolbox(Works, 2012; Delorme and Makeig, 2004). To compare the values of EEG spectra for the three conditions repeated measures ANOVA was used followed by post-hock analysis using t-test. To compare the frontal asymmetry for left (F7, F3, AF3, FC5) vs right (F8, F4, AF4, FC6) frontal electrodes a t-test was performed. A significance level of .05 was chosen and Bonferroni correction was applied to counteract the problem of multiple comparisons. The data was also inspected for the violation of normality and sphericity assumptions.

3.6 Results

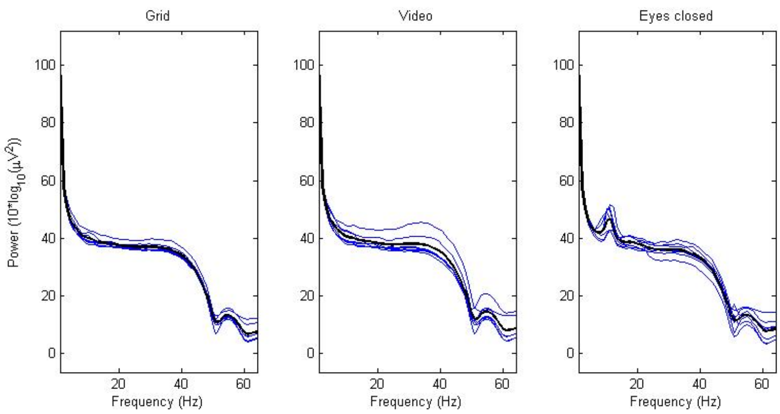

Figure 3.2: Comparison of averaged EEG bands for all electrodes and all three conditions (grid, video, eyes closed). No significant results were found.

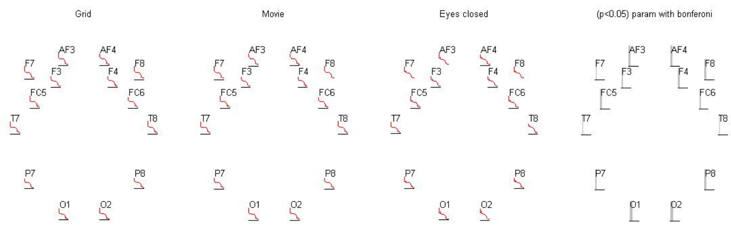

Figure 3.3: Comparison of EEG bands for each electrode and all three conditions (grid, video, eyes closed). Significant results were found for each electrode.

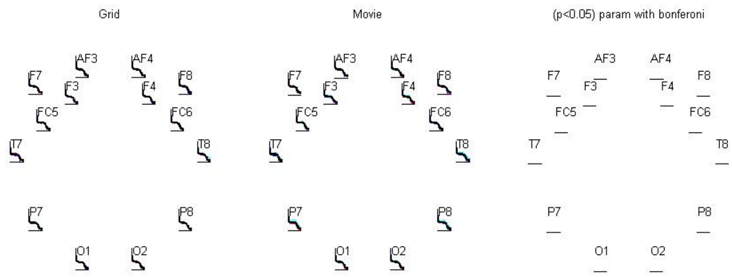

Figure 3.4: Post-hoc comparison of EEG bands for each electrode for conditions grid and video. No significant results were found.

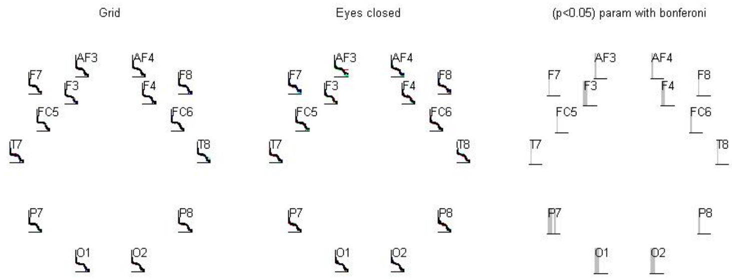

Figure 3.5: Post-hoc comparison of EEG bands for each electrode for conditions grid and eyes closed. Significant results were found for all electrodes.

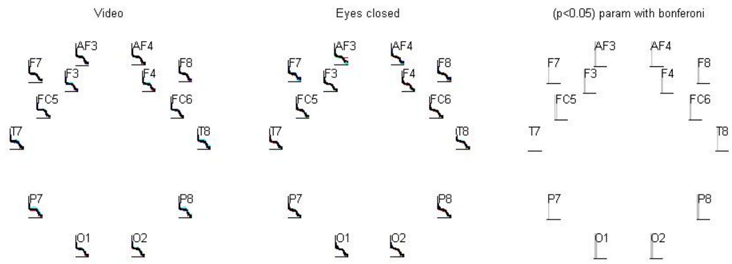

Figure 3.6: Post-hoc comparison of EEG bands for each electrode for conditions video and eyes closed. Significant results were found for all electrodes except T7.

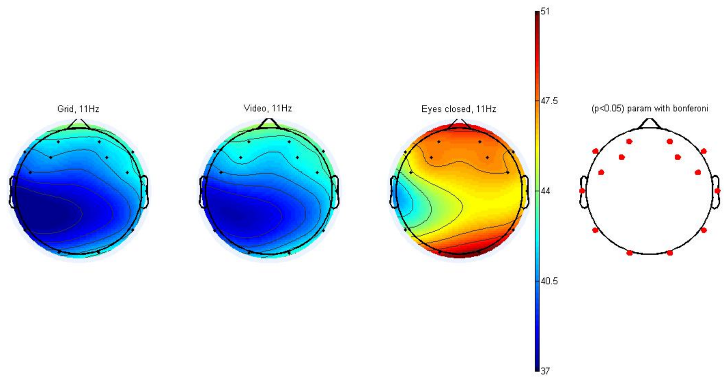

Figure 3.7: Topgraphy plot at 11Hz, for all conditions with statistical comparison. Significant results were found for all electrodes.

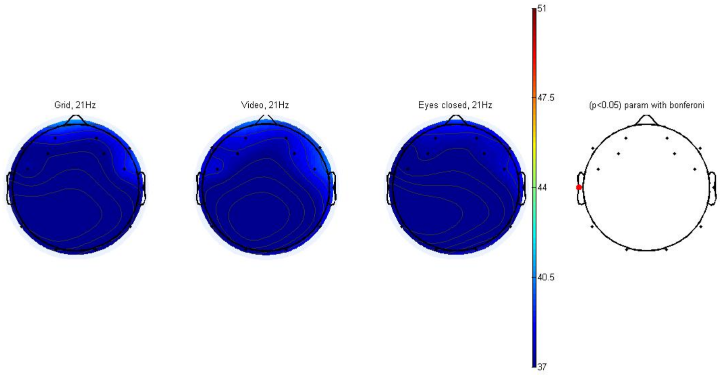

Figure 3.8: Topgraphy plot at 20Hz, for all conditions with statistical comparison. Significant result was found only for on electrode T7.

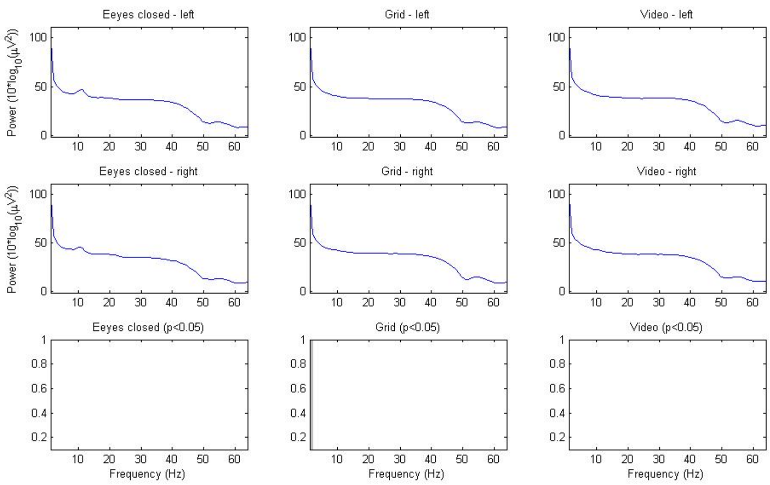

Figure 3.9: Comparison of EEG bands for left (F7, F3, AF3, FC5) vs right (F8, F4, AF4, FC6) frontal electrodes and all three conditions (grid, video, eyes closed). No significant results were found.

Repeated measures analysis of variance ANOVA (grid vs. video vs. eyes closed) showed significant differences for all electrodes across the scalp (see Figure 3.3). Post-hoc analysis showed significant results for grid vs. eyes closed and video vs eyes closed conditions (Figures 3.5) and 3.6) and no significant results for grid vs. video (Figure

3.4. The significant results were mostly in the range of alpha power which is demonstrated in Figure 3.7. Comparison between left and right frontal activity showed no significant results for any condition and any electrodes (Figure 3.9). The variance in amplitude between the three conditions was also compared using F-test of equality of variances and showed no significant results.

Repeated measures analysis of variance ANOVA was performed to compare the power at frequency of 11 Hz ($F(2,7) = 14.85$, p ¡ 0.001). The averaged values of power at frequency of 11 Hz were as follows: eyes closed - 41.598, grid - 40.8588, video - 46.6733.

To compare the participants' reported level of relaxation a repeated measures analysis of variance ANOVA (before the recording vs. grid vs. video vs. eyes closed) was performed. No significant differences were found ($F(3,7) = 2.28$, $p = 0.11$).

3.7 Conclusions

The results show the participants did not gain a higher level of relaxation during grid condition as compared to video and eyes closed conditions. Neither the spectrum analysis (Fig. 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8) nor the analysis of frontal asymmetry (Fig. 3.9) indicated a difference between the conditions. The analysis of participants' pen and paper responses also did not show the pattern. The significant result obtained is the higher level of alpha for eyes closed, which is typically observed when people close their eye for a longer period of time. The feedback provided to the participants did not result in higher state of relaxation. The reason for this may be the type of feedback used. Some participants commented that they did not feel that they had influence over the shape of the road network and did not feel that their actions or mental state had any influence on the state of the road network. More direct and simpler feedback, easier to understand for participants could provide in better results as well as the use of better EEG equipment could make a difference. Moreover, the measure of meditation used for on-line feedback was provided by Emotiv Engine and it is unknown how it was calculated. It is therefore unknown how accurate the on-line feedback was and how closely the on-line feedback corresponded to the measures used in the off-line analysis.

Chapter 4

Experiment 2

4.1 Introduction

As BCI illiteracy affect a large proportion of potential BCI users and may become an obstacle in the popularization of BCI technology, in the second experiment we decided to investigate the potential factors affecting BCI illiteracy. In this experiment we investigated the relation between P300-based BCI performance and attention. In particular, with a view to investigating inter-individual differences in the ability to control a P300-based BCI system and the role played by attentional abilities, we recorded the users' performance when interacting with a tailored BCI system and measured their attentional abilities along several dimensions, including temporal attention, which refers to the ability to allocate processing resources over time, and three components of the attentional system: alerting, orienting and executive attention (Posner and Petersen, 1990). The results of two behavioural tasks were correlated with performance on P300-based BCI. We hypothesise that better results in attentional blink task as well as score in executive attention will correlate with better classification accuracy on BCI task.

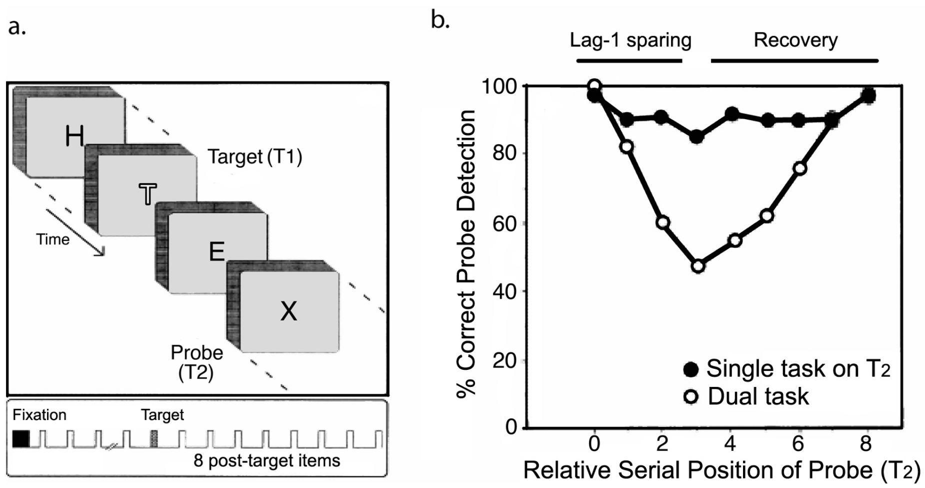

Figure 4.1: Adapted from Raymond et al. (1992) demonstrating the Attentional Blink. Panel a. Participants' time dubbed "Lag-1 sparing". After the blink has occurred, the cognitive system slowly recovers. The single task condition is a control condition in which participants are asked to respond to T2 while ignoring T1.

1. The attentional blink is an effect observed when participant are presented with items of information rapidly flowing on the screen (rapid serial visual presentation, RSVP), and occurs when the participant is asked to perform a task on one particular target (see 4.1). As the participant is detecting and processing the target, they are unable to detect and process the second target if it follows the first target in a window of time for about 300-500 msec Raymond et al. (1992). This behavioural task provided a measure of the participants' ability to switch context rapidly, which is a

critical ability when interacting with a P300-based BCI system.

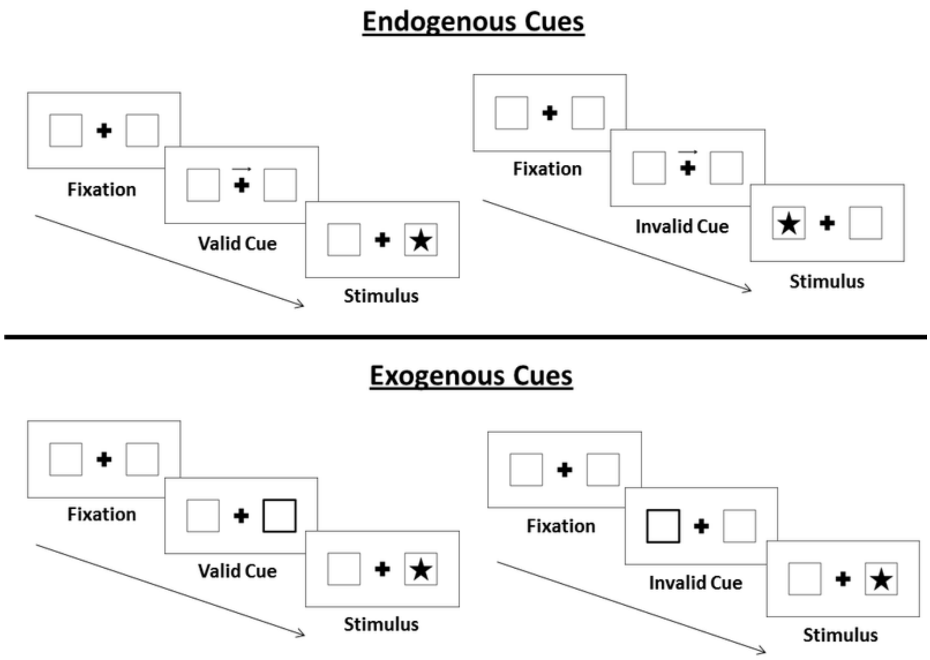

Figure 4.2: Representation of endogenous and exogenous cues in the Posner Paradigm.

2. The Posner cueing requires the participant to detect a particular target, flanked with congruent or incongruent cues. Their ability to perform can be broken down along three dimensions - alerting, orienting and executive attention - by way of subtracting the participant's results when they undergo different experimental conditions. Participants are seated in front of the computer and instructed to focus their eyes on the fixation cross. After a short period of time a cue is displayed on the screen. Shortly after the cue is removed, the stimulus appears and participant is asked to respond by pressing a key on the keyboard. The reaction time is measured and analysed Posner (1980).

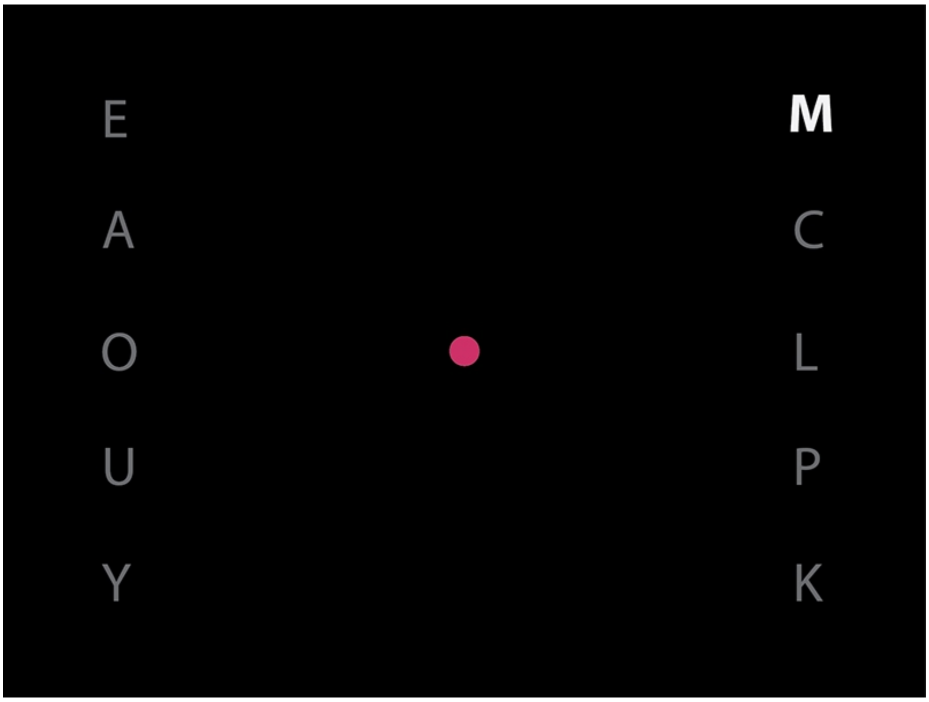

Figure 4.3: Representation of display used in the experiment

The results of behavioural tasks were correlated with the performance of the BCI task described in section 4.4 and the results are presented in section 4.6.

4.2 Participants

Twenty eight participants took part in the experiment. The average age of participants was 33.2 years. The group consisted of 17 males and 11 females. All participants had correct or corrected to normal vision and no neurological disorders which could affect the use of BCI.

4.3 Experimental Setup

The experimental setup consists of a PC computer and Emotive EEG device. The experiment was implemented using TOBI Signal Server (TOBI Signal Server), Psychtoolbox (Psychtoolbox) and everything was integrated in Simulink (Simulink). The Simulink model is presented in Figure 4.4.

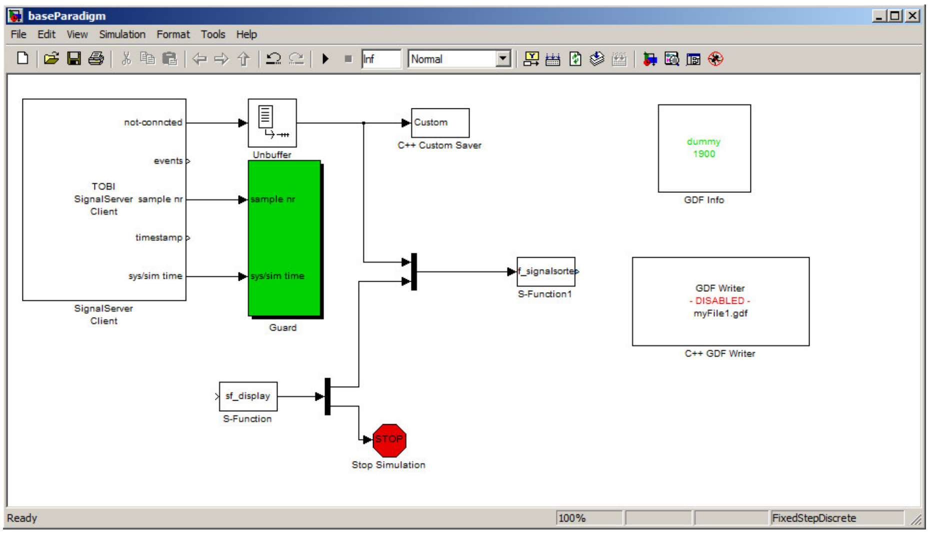

Figure 4.4: Simulink model used in the experiment

4.4 Experimental Procedure

During experiment participants were seated in front of the computer and performed three tasks. Two behavioural measures of attention described above (section 4.1) and a BCI task during which participants were required to concentrate on and count a particular letter to move the red ball to either left or right while the letters were flashing in random, unpredictable order (see Figure 4.3). This task used so called oddball paradigm described in section 2.10.2. Participants efficiency in performing this task was assessed in an off-line analysis using BLDA described below.

4.5 Data Analysis

4.5.1 Pre-processing

Before applying the classification function, a number of pre-processing operations were applied to the data. The operations were applied in the following order.

1. Referencing

   The signal was referenced to the mean of all electrodes.

2. Filtering

   The data were filtered using fifth order forward-backward Butterworth low pass filter with cut-off frequency of 100Hz. Using a forward-backward filter allows to filter the data while avoiding the phase shift which is very important in case of time locked effect like P300. The filter was implemented using MATLAB function butter and to create the filter and the function filtfilt was applied for filtering.

3. Trial extraction

   Single trials of 500 msec were extracted. The trials started at the stimulus onset and the stimuli were intensified for 100 msec. The interstimulus interval (ISI) was 400 msec, therefore the trials did not overlap.

4. Downsampling

   The EEG data was acquired to 128 samples (64 samples per 500 msec epoch) and downsampled by the factor of two to (32 samples per epoch).

5. Windsorizing

   Muscle activity and eye movements create large artefacts in the EEG signal. To reduce the effects of these artefacts, the data from each electrode were windsorized. For samples from each electrode the tenth and ninetieth percentiles were computed. Values lying outside this range were replaced with 10th and 90th percentile respectively.

6. Normalisation

   The data from each electrode was scaled to the interval from -1 to 1.

7. Feature vector construction

   The EEG signal from the selected channels (electrodes) was concatenated into a feature vector.

4.5.2 Classification method

Classifier values were trained on the data from two first sessions and validated on two left out sessions. Bayesian Linear Discriminant Analysis (BLDA) based on Fisher's Linear Discriminant Analysis (FLDA) was used to learn the classifier. Fisher's linear discriminant analysis is a methods used in statistics, machine learning and pattern recognition. LDA finds a linear combination of features which best separates two or more classes of objects (Hoffmann et al., 2008).

BLDA is an extension of FLDA. BLDA regularization is used to prevent over-fitting to high dimensional and noisy datasets. Through a Bayesian analysis allows to estimate the degree of regularization automatically from training data without the need for time consuming cross-validation.

4.6 Results

4.6.1 Dual-target rapid serial visual presentation task

The averaged results of dual-target RSVP task are shown in Figure 4.5. The curve represents the accurate T2 report given correct T1 identification as a function of lag times. The results show a typical attentional blink result with decreased T2 identification when the temporal separation between T1 and T2 is approximately 200 msec. The T2 identification rate improves when the temporal separation increases. The decrease in T2 identification rate at the lag time of 800 msec is unusual and can probably be explained by participants not expecting (not looking for) T2 so long after T1.

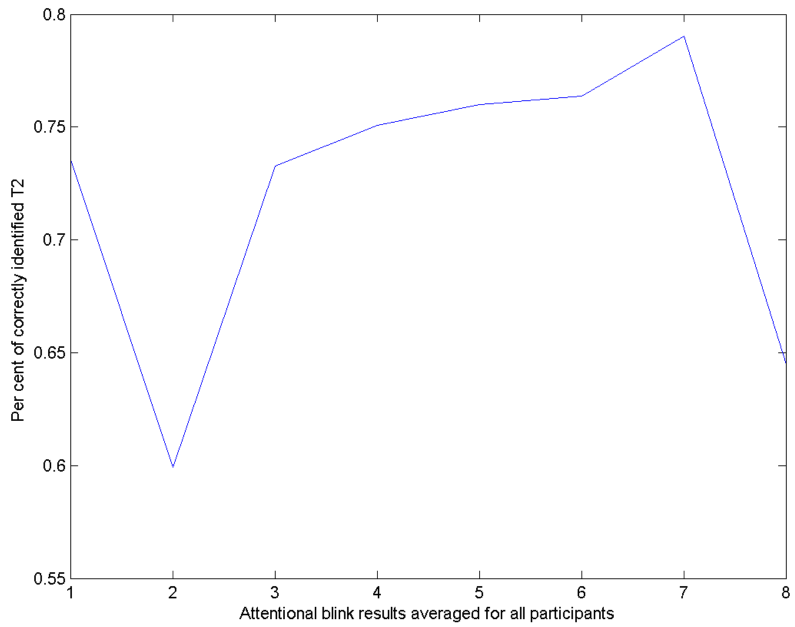

Figure 4.5: Averaged results of attentional blink for all participants. X axis corresponds to participants and Y axis shows the percentages of correctly identified target two.

4.6.2 Posner cueing task

The results of attention detection task have been used to compute three measures of attention: alerting, orienting and executive attention.

1. Alerting was calculated by subtracting the reaction time for uncued trials form the reaction time for congruent trials.

2. Orienting was calculated by subtracting the reaction time for congruent trials with special cue from the reaction time for congruent

trials with central cue.

3. Executive attention was calculated by subtracting the reaction time for congruent trials from the reaction time for incongruent trials.

The results for alerting, orienting and executive attention are presented in Figure 4.6.

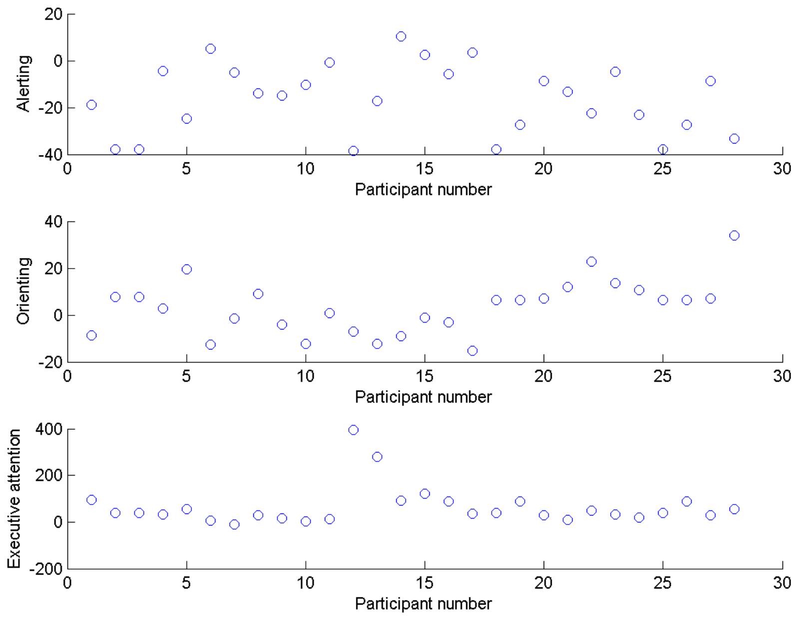

Figure 4.6: Results of Posner cueing task. The figures show distribution of results of all participants alerting, orienting and executive attention from top to bottom. X axis corresponds to different participants and Y axis shows the difference in reaction times for each of the contrasts described in section 4.6.2.

4.6.3 Classification Results

Classification has been obtained for two electrode configurations. One includes all electrodes and the second included four occipital and parietal electrodes (P7, P8, O1, O2). The configurations are show in Figure 4.7. The electrodes were chosen due the fact that P300 effect is the most pronounced in the parietal and occipital area of the brain.

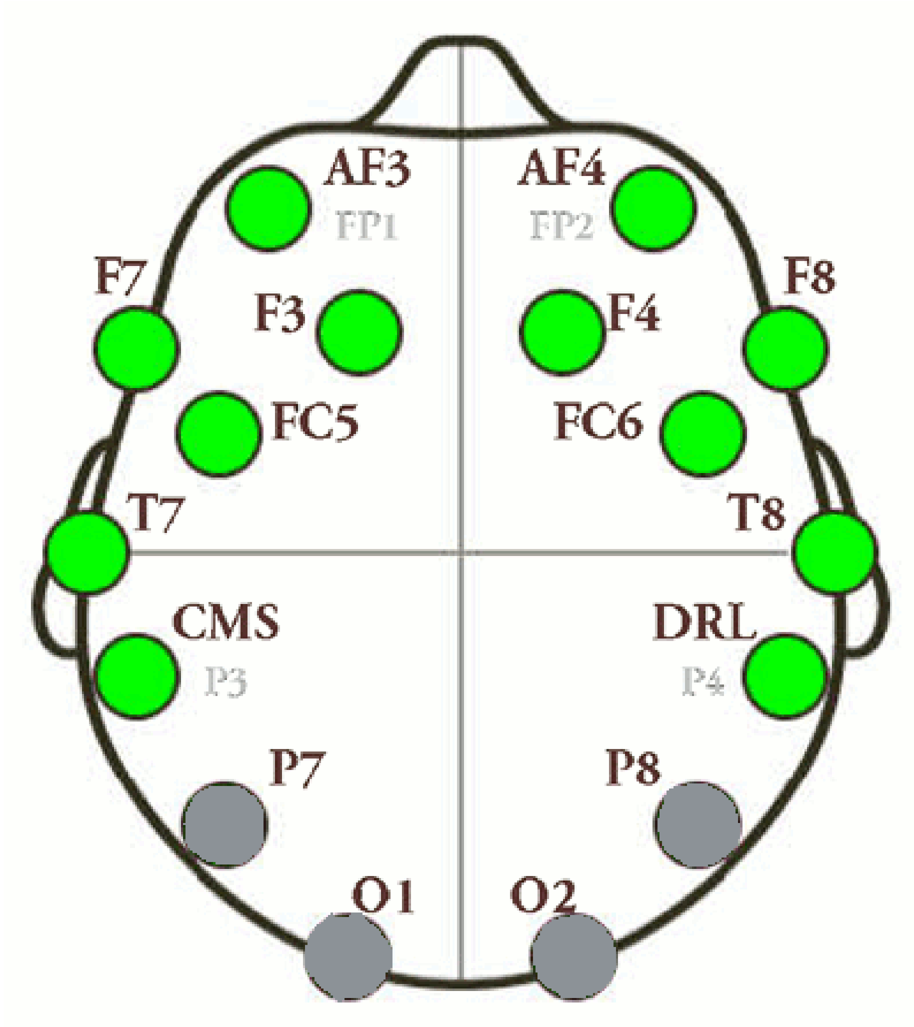

Figure 4.7: Electrodes included in the electrode configuration are shown in grey.

Classification results obtained from all electrodes were compared with the classification results obtained from the set of four electrodes (see Figure 4.8). Paired Sample t-test showed significantly better result for all-electrode configuration ($t(27) = 2.1635$, $p = 0.035$), therefore all remaining analysis was conducted using all-electrode configuration.

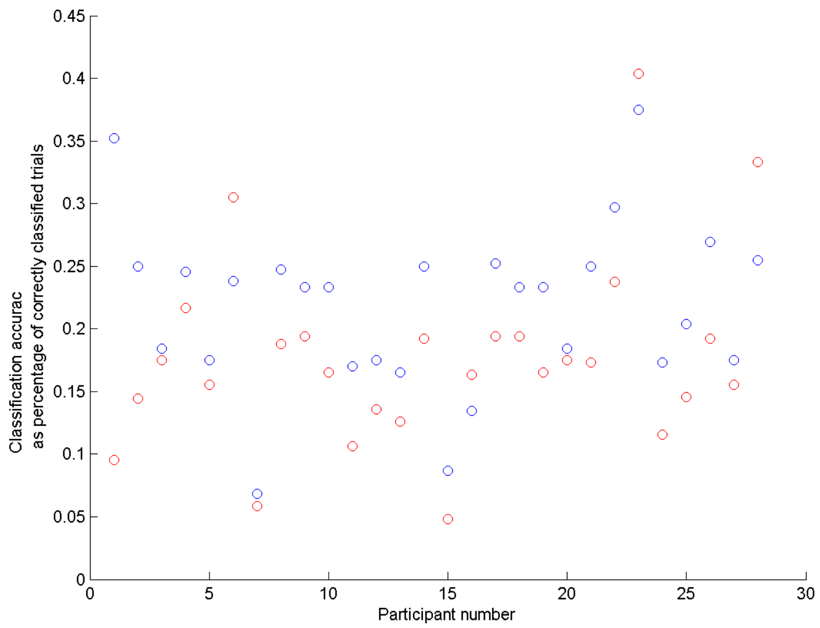

Figure 4.8: Classification accuracy for all participants as a percentage of correctly classified trials. Red - four-electrode configuration, blue - all-electrode configuration.

4.6.4 Relation between classification accuracy and measures of attention.

Pearson's R correlation was computed to determine the relationship between the measures attention obtained using Posner cueing task and classification accuracy. The scatter plots of these results are shown in Figures: 4.9 - alerting, 4.10 - orienting and 4.11 - executive attention.

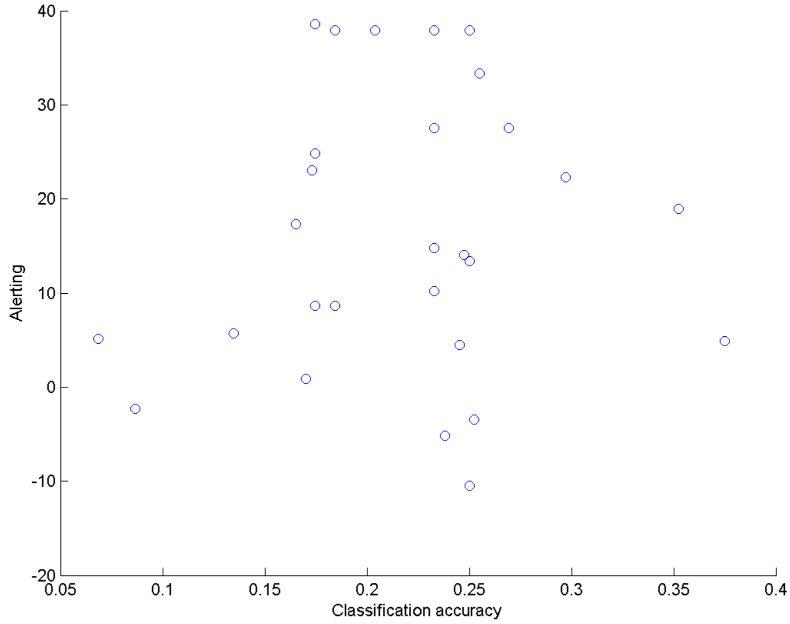

Figure 4.9: Classification accuracy for all participants as a percentage of correctly classified trials and the measure of alerting obtained using Posner cueing task.

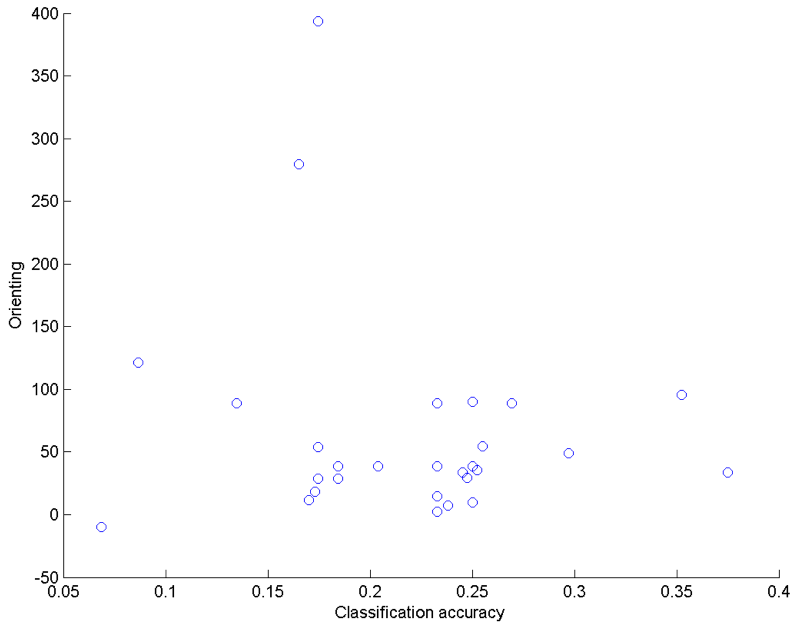

Figure 4.10: Classification accuracy for all participants as a percentage of correctly classified trials and the measure of orienting obtained using Posner cueing task.

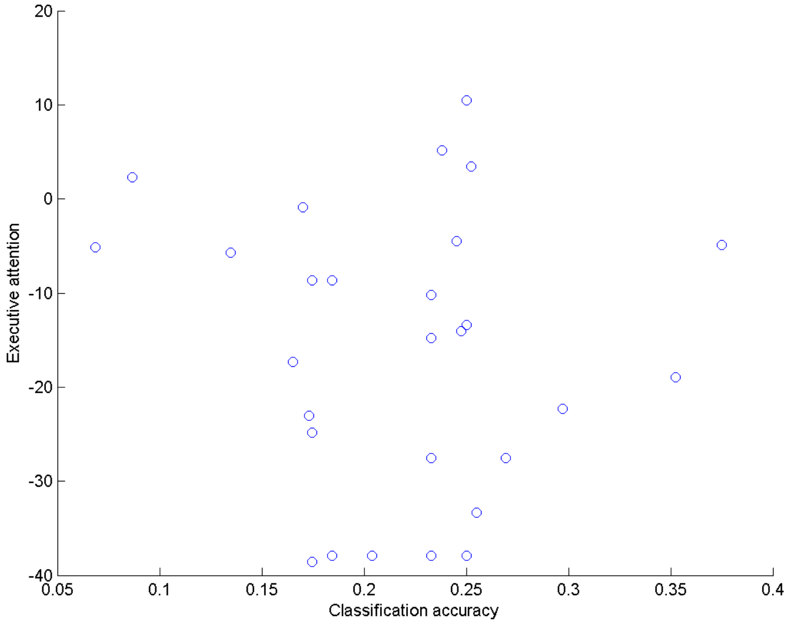

Figure 4.11: Classification accuracy for all participants as a percentage of correctly classified trials and the measure of executive attention obtained using Posner cueing task.

The values for correlation of variables classification accuracy and alerting were (r = 0.09 , p = 0.64). Correlation of variables classification accuracy and orienting produced values of (r = -0.15, p = 0.43). The parameters for correlation of variables classification accuracy and executive attention were (r = -0.15, p = 0.43). None of the correlations mentioned above were significant.

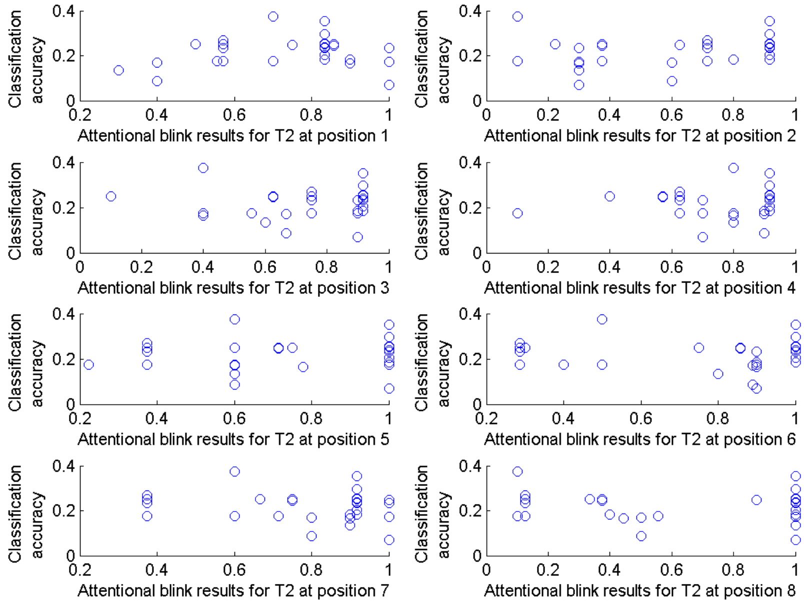

Figure 4.12: Correlation results for dual-target rapid serial visual presentation task and classification accuracy with each of the T2 positions (lag times).

T2 lag time	Pearson's R	Significance (p)
100 msec	0.16	0.40
200 msec	0.22	0.27
300 msec	-0.003	0.99
400 msec	0.05	0.78
500 msec	0.07	0.71
600 msec	-0.09	0.65
700 msec	-0.17	0.39
800 msec	-0.08	0.69

Table 4.1: Correlation results for dual-target rapid serial visual presentation task and classification accuracy.

For dual-target rapid serial visual presentation task classification accuracy was correlated with each of the T2 positions (lag times). The exact results are shown in Figure 4.12 and Table 4.1. No significant correlations were obtained.

4.7 Conclusions

The obtained results do not support the hypothesis that attention is an important factor influencing P300-BCI performance. The other factors discussed in section 2.10.2 may play a more important role in determining who is able to control P300-based BCI. The other reason why the correlations are not significant may be the fact that none of the participants obtained a very good BCI control (M = 0.2182, SD = 0.0672). This relative concentration of the results make it difficult to obtain significant correlation. The fact that classification accuracy was obtained using off-line analysis might also have influenced the results. The inaccuracy of the on-line feedback provided to the participants might have influenced their motivation and attention and this in turn might have changed the shape of their P300 response making the correct responses difficult to classify.

Chapter 5

Conclusions and Future directions

In this chapter the conclusions from the results are presented, followed by discussion and proposed future directions.

5.1 Conclusions

The results of experiment one showed that participants did not obtain the higher level of relaxation during grid condition as compared to video and eyes-closed conditions.

The results of experiment two indicate that attention may not be the factor defining performance on P300-based BCI systems. It does not, however, exclude the possibility that it may play an important role in other BCI paradigms, especially SMR-based BCI.

5.2 Limitations

One of the reasons for insignificant results in experiment one may be the type of feedback used which was not easily understandable by the participants. A simple and more direct feedback may deliver better results. Users without prior training participated in this experiment, obtaining significant results may require extensive practice. Longer sessions may also be required to induce the state of relaxation.

In case of experiment two the use of different classification algorithms for on-line and off-line analysis might have substantially influenced the results. The algorithm use during the experiment was much simpler then the algorithm used in the off-line analysis, therefore the feedback provided to the users was much less accurate. This was done due to the hardware limitations.

5.3 Future directions

The use of BCI technology for rehabilitation and metal training is an interesting and promising field of BCI application. The success of these systems depends on quality of each constituent part. Embedding feedback in engaging virtual environment and using computer game technology will make them more entertaining which can increase their efficiency. BCI systems for training different mental abilities (e.g. relaxation, concentration, meditation) can be imagined. A general framework for these kind of systems would consist of two stages. In the first stage a brain patters for a particular mental state (e.g. relaxation) typical for is recorded while participant is induced into this state using other methods (e.g. massage, meditation) After that, in the BCI stage, a feedback is provided for the user which shows how different the user's pattern of activity is from the desirable pattern recorded in the first stage. Using this approach allows us to tailor the BCI system for each user. Particular mental states are correlated with typical patterns of brain activation. However, due to individual differences in brain morphology and physiology these patterns are different for different users. Using one general pattern for all users may make the task of matching the user's pattern with the general pattern extremely difficult or even impossible. This may cause frustration and discourage users from using BCI.

The search for factors influencing the BCI performance will continue and the biological and morphological factors will need to be taken into account. Other neuroimaging techniques (e.g. fMRI) coupled with EEG-based BCI can provide more information about the biological and morphological factors that influence BCI performance. A series of experiments can be proposed that combine the use of EEG, fMRI and MRI technology together with experimental measures of attention to examine the influence of the aforementioned factors on BCI performance. This could give us the understanding which of the factors are important and have influence on the BCI performance and whether BCI illiteracy can be "cured" by influencing the psychological factors (e.g. attention training). The use of BCI systems with better on-line classification and better feedback will provide more ecologically valid experimental conditions which may influence users' attentional processes and affect the classification accuracy.

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Appendices

Appendix A

Consent Form for Experiment 1

Participant's Consent Form

You are about to participate in an experiment investigating the use of a brain-computer interface technology to enhance the experience of contemplative meditation. We are going to use the Emotiv Epoch headset, which has been presented to you. The experiment will take about an 1 hour. There will be three sessions and you will be presented with different forms of visual stimuli.

1. Brid - based road network.
2. Watching a movie.
3. No visual stimuli - eyes closed.

This research is conducted by Mr Szymon Fialek (Coventry University), with Dr Fotis Liarokapis (Coventry University), Dr Chris Peters (KTH Royal Institute of Technology, Sweden) and Dr Etienne Roesch (University of Reading).

		Please Initial in the box
1.	I confirm that I have read and understood the information presented to me, and have had the opportunity to ask questions.	☐
2.	I understand that my participation is voluntary and that I am free to withdraw at any time, without giving a reason.	☐
3.	I agree to take part in the above study.	☐
4.	I agree for my data to be analysed and published.	☐

Name of Participant …………………… Date …/…/…… Signature ………………..

Name of Researcher …………………… Date …/…/…… Signature ………………..

Appendix B

Question List for Experiment 1

Thank you for participation.

We would like to take this opportunity to ask you a few questions.

1. Who relaxed did you feel during each of the sessions? Answer on the scale from 1 – 10, where 1 – not at all; 10 – very relaxed.

Session 1:
....

Session 2:
....

Session 3:
....

2. How relaxed do you feel now? Answer on the scale from 1 –10:

....

3. Did you feel there was a link between how you felt at the time and what was being displayed on the screen? Please explain:
....
....
....

3. How comfortable did you feel using the Emotiv Epoch headset? Answer of the scale from 1 – 10 and describe if you wish:
....
....
....

4. Do you have any other comments?
....
....
....

If you wish to withdraw from the study and want you data to be deleted please contact:

Mr Szymon Fialek at fialeks@coventry.ac.uk

Appendix C

Subject Information Form for Experiment 2

University of Reading

Recording EEG to investigation into illiteracy in P300-based BCI

Subject Information

Name:

Date of Birth:

Gender: male / female

Handedness: right handed / left handed

If yes please provide further details:

Signature: Date:

Investigator Contact Details:

Dr. Etienne Roesch

e: e.b.roesch@reading.ac.uk

Szymon Fialek

e: s.fialek@reading.ac.uk
m: 07946 777 564

Appendix D

Consent Form for Experiment 2

ANNEX C

Research Ethics Committee

University of Reading

Consent Form

1. I have read and had explained to me by **Szymon Fialek** the accompanying. Information Sheet relating to the project: 'Investigation into illiteracy in P300-based BCI.'

2. I have had explained to me the purposes of the project and what will be required of me, and any questions I have had have been answered to my satisfaction. I agree to the arrangements described in the Information Sheet in so far as they relate to my participation.

3. I understand that participation is entirely voluntary and that I have the right to withdraw from the project any time, and that this will be without detriment to any care or services I may be receiving or may receive in the future.

4. This application has been reviewed and approved by the Head of the School of Systems Engineering and has been given a favorable ethical opinion for conduct

5. I have received a copy of this Consent Form and of the accompanying Information Sheet.

6. I confirm that I do not suffer from epilepsy, never had a seizure nor have a history of seizure in immediate family.

Name:

Date of birth:

Signed:

Date:

Investigator Contact Details:

Dr. Etienne Roesch
e: e.b.roesch@reading.ac.uk

Szymon Fialek
e: s.fialek@reading.ac.uk
m: 07946 777 564

Appendix E

Information sheet for Experiment 2

University of Reading

Recording EEG to investigation into illiteracy in P300-based BCI

Subject Information

Name:

Date of Birth:

Gender: male / female

Handedness: right handed / left handed

If yes please provide further details:

Signature: Date:

Investigator Contact Details:

Dr. Etienne Roesch

e: e.b.roesch@reading.ac.uk

Szymon Fialek

e: s.fialek@reading.ac.uk
m: 07946 777 564

Appendix F

Ethics Information Sheet for Experiment 2

Research Ethics Committee

University of Reading

Information sheet

Project:

Investigation into illiteracy in P300-based BCI.

School:
School of Systems Engineering

Department:
Cybernetics

Principal Investigator:

Dr. Etienne Roesch (e.b.roesch@reading.ac.uk)

Other investigators

Szymon Fialek (s.fialek@reading.ac.uk)
Dr Fotis Liarokapis (aa3235@coventry.ac.uk)

Date of study commencement:
1st July 2013

Outline:

The purpose of this second experiment is to investigate the relation between P300-based BCI performance and attention. In particular, with a view to investigating inter-individual differences in the ability to control a P300-based BCI system and the role played by attentional abilities, we will record the users's performance when interacting with a tailored BCI system and measure their attentional abilities along several dimensions, including temporal attention, which is refers to the ability to allocate processing resources over time, and three components of the attentional system: alerting, orienting and executive attention.

Appendix G

Towards Procedurally Generated Perceptually Plausible Inhabited Virtual Cities: A Psychophysical Investigation

Thus paper has been removed. The unabridged version of the thesis can be viewed at the Lanchester Library, Coventry University