ADAPTIVE BRAIN COMPUTER INTERFACE (BCI) WITH ATTENTION VARIATIONS

WORKSHEETS

2nd Semester Master
Biomedical Engineering and Informatics

Project Group: 8404

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Contents

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STUDENT REPORT

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Title:
Adaptive Brain Computer Interface with Attention Variations

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Synopsis:

Attention is a crucial parameter for inducing plasticity in stroke patients. Shift of attention are infrequent during experimental setting but are commonly present in clinical setting. Brain Computer Interface (BCI) systems rely heavily on attention during information processing. The aim of this study was to evaluate the effect of visual, real-time feedback in subjects attention. Eleven healthy subjects participated in a crossover study setup with two sessions: without feedback and with feedback. During these sessions, subjects were asked to perform ankle dorsiflexion (main task), while counting oddball tone sequences (secondary task to divert the attention). Therefore, two different attention states were recorded in each session (focused and diverted attention from the main task). Accuracy, True Positive Rate (correctly classified diverted attention trials) and True Negative Rate (correctly classified focused attention trials) were calculated after the two sessions to evaluate subjects' performance. Results showed $51.11 \pm 9.39\%$ mean accuracy, $49.33 \pm 19.60\%$ mean TPR, $52.89 \pm 23.98\%$ mean TNR for the without feedback session; whereas for the feedback session, were $57.33 \pm 8.00\%$ mean accuracy, $52.44 \pm 20.24\%$ mean TPR, $62.22 \pm 22.73\%$ mean TNR. Repeated measures ANOVA showed no significant difference for neither TPR nor TNR. The little variation in TPR suggest that concentration is not increase during the oddball trials, but the increase in TNR during the feedback session implies that feedback helped the subjects to understand the paradigm and increase the accuracy with respect to the without feedback session. Therefore feedback increases the concentration on the experiment but not on dorsiflexion exclusively.

Preface

This semester project has been made by students from Biomedical Engineering and Informatics from Aalborg University in a period from the 1st of February until the 2th of June 2017. The theme for the project was "Biomedical Signals and Information". The aim of the project was to work on BCI systems and develop an online paradigm to show the effect of feedback on attention diversion.

Aalborg University, 2th of June 2017

Chapter 1

Anatomy and Physiology

1.1 The nervous system

The nervous system is made by all nerve cells in the human body and its extreme importance is given by the fact that allows the communication of information from the brain to virtually all the body parts and viceversa. The nervous system is the means by which we intend to move and we deliver the intention to the muscles responsible for the action. It is basically subdivided into central, peripheral and autonomic nervous system. On the following pages, an introduction to central and peripheral nervous system will be given. The central nervous system is made by brain and spinal cord. The brain acts as central processor for pieces of information brought by the spinal cord. At the brain level, inputs are received and at cortical level they are converted into perception. These perceptions might activate a response that will travel from the brain to the effectors located at the periphery on the controlateral side. Decussation is when a stimulus travelling from the center to the periphery (or vice versa), changes side along the nervous system. For example, a pinch on the right hand will be interpreted on the left side of the brain. In the same way, a motor command coming from the left side of the brain will be directed to a right sided extremity in the body.[1]

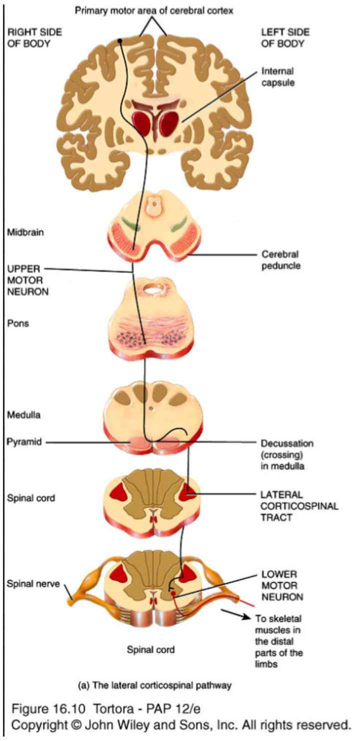

Figure 1.1: Decussation of a stimulus from the point of stimulation to the brain.

1.2 The brain

As previously mentioned, the brain is the central processing unit of the body. The brain is a spongy organ made up of nerves and supportive tissues located in the head. The lower part of the brain is connected to the spinal cord. The brain has three main parts: cerebrum, cerebellum and brainstem.[2] The cerebrum is the largest part of the brain. It is divided into two halves called the “left” and “right” cerebral hemispheres. The two hemispheres are connected by a bridge of nerve fibres called the “corpus callosum”. The right hemisphere is known to control the left side of the body while the left hemisphere is known control the right side of the body. The outer surface of the cerebrum is called "cerebral cortex" or "grey matter". It is the area of the brain where nerve cells make synapses. The inner area is defined as "white matter" because the insulation around the axons appears white.[2] The cerebrum is further divided into four sections called lobes. These include the frontal (front), parietal (top), temporal (side) and occipital (back) lobes. Each lobe has different functions:

- The frontal lobe controls movement, speech, behaviour, memory, emotions and intellectual functioning, such as thought processes, reasoning, problem solving, decision making and planning.

- The parietal lobe controls sensations, such as touch, pressure, pain and temperature. It also controls spatial orientation (understanding of size, shape and direction). Furthermore it is involved in sensory integration.

- The temporal lobe controls hearing, memory and emotions. The left temporal lobe also controls speech.

- The occipital lobe controls vision.

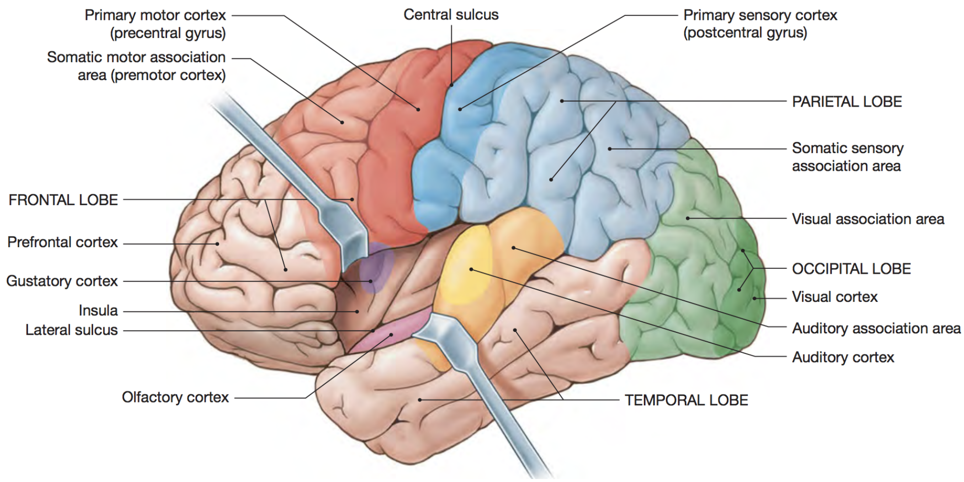

Figure 1.2: Gross Anatomy of the Brain. Source:Foundamental of Human Anatomy and Physiology. 9th Edition. Martini and Nath

1.3 Motor Cortex

Many areas in the brain are related to human movement, one of the most important is the primary motor cortex (M1). M1 is located in the frontal lobe, along with the precentral gyrus. The role of the primary motor cortex is to generate impulses aimed to control the execution of movement. Signals from M1 decussates to activate skeletal muscles on the opposite side of the body. The body is somatotopically represented on the motor cortex, for example the foot is next to the leg which is next to the trunk which is next to the arm and the hand . The amount of brain involved with a body part represents the amount of control that the primary motor cortex has over that body part. For example, a lot of cortical space is required to control the complex movements of the hand and fingers, and these body parts have larger representations in M1 than the trunk or legs. This disproportion of the body map on the motor cortex is known as motor homunculus (shown in figure).

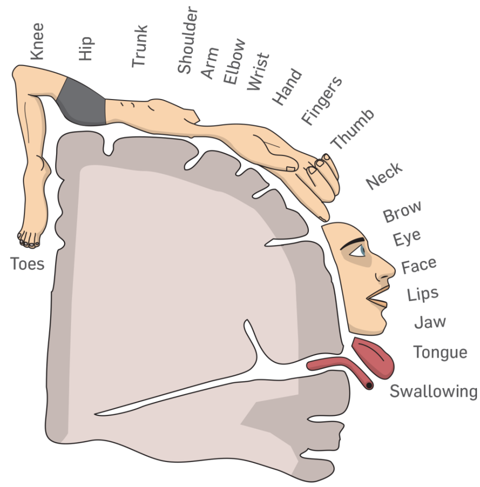

Figure 1.3: Representatin of the Homunculus. Source: Max Planck Florida Institute for Neuroscience

1.4 Brain Waves

Cortical activity is associated with neuron postsynaptic potentials. When multiple neurons fire at the same time and in synchrony, the firing effects sums up and generates an electric field, which propagates throughout a volume conductor made of brain tissue, skull, skin and hairs. The electrical field can be measured from the scalp via EEG measuring systems. Brain waves have 3 important physical descriptors. Frequency: is the speed of an oscillation and it's measured in Hertz (Hz), indicating the number of oscillations per second. Power: is the amount of energy in a frequency band. Phase: The phase is the amount of synchronisation across firing neurons. Billions of neurons in the human brain have complex firing patterns. Neural oscillations that can be measured with EEG are even visible in raw, unfiltered, unprocessed data. These oscillations are a mix of many oscillations which correspond to states different states of the brain. These frequencies are classified based on frequency ranges, also known as frequency bands: Delta band (1–4 Hz), Theta band (4–8 Hz), Alpha band (8–12 Hz), Beta band (13–25 Hz) and Gamma band (>25 Hz).[3]

1.4.1 Delta Waves

Delta waves are the slowest and highest amplitude among the brainwaves. They oscillate in between 1 and 4 Hz [3]. Delta waves are only present during deep non-REM sleep. The stronger the delta rhythm, the deeper the sleep. It has been shown that Delta frequencies are stronger in the right brain hemisphere and since sleep is associated with memory consolidation, delta frequencies play a key role in acquiring skills and learning information.

1.4.2 Theta Waves

Theta waves have a frequency of oscillations within the 4–8 Hz frequency range [3]. Theta frequencies become stronger with increasing task difficulty. Theta waves have been associated with brain processes under mental workload or working memory [4][5]. It has been suggested that theta waves serve as connections of brain regions located further apart, during cognitive processes.[6]

1.4.3 Alpha Waves

Alpha is defined as rhythmic oscillatory wave with a frequency range of 8–12 Hz [3]. Alpha waves are generated in posterior cortical sites, including occipital, parietal and posterior temporal brain regions. Alpha waves reflects activities related to sensory, motor and memory functions. On the other side, alpha waves power is greatly reduced during mental activities or activities involving body movement. Alpha brain waves suppression are a strong mark suggesting engagement and focused attention towards any type of stimulus [7]. Furthermore, Alpha waves are used for comparing relaxation state induced by meditation in experienced versus beginner meditators[8] Attention is closely related to alpha power.Distracted subjects generally show higher amounts of alpha wave power in experimental settings [9]

1.4.4 Beta Waves

Beta waves oscillates within the 12–25 Hz range [9]. This frequency is generated both in posterior and frontal regions. Along the motor cortex beta wave power becomes stronger in relation to the execution of a movement, especially with fine movements requiring attention. It has been suggested that the brain mimics the movements of people that we observe, thus indicating the presence of a “mirror neuron system” in the brain which is coordinated by beta frequencies.

1.4.5 Gamma Waves

It is yet to be clarified where exactly in the brain gamma frequencies are generated and what these oscillations actually mean. Some theories say that gamma, similar to theta, serves as a link to several sensory impressions of an object and therefore attention. Other theories argue that gamma waves are a byproduct of other neural processes such as eye-movements and therefore do not actually express cognitive processing at all. Further studies are needed to clarify the meaning of gamma waves.

Chapter 2

Attention

2.1 Attention

According to William James (psychologist and philosopher), attention is controlling the mind and select to deal with some tasks instead of others. Attention can be thought as a highlighter among our tasks, the highlighted ones stand out from the rest. As you read through a section of text in a book, the highlighted section stands out, causing you to focus your interest on that area. But attention it is also a filter when competing stimuli present to the body and it focuses more on certain stimuli instead of others because they are not relevant at the moment. In this way the body can focus its resources on important information. Studies have demonstrated that attention is limited in terms of capacity and duration. [10][11] Attention plays a key role in subject undergoing a therapy since if attention is low then no plasticity is evoked, irrespective of the correct association between the intent and the reproduction of that movement[12]

2.1.1 Attention Shifting

Shift of attention occurs when there is a wanted increasing in focus on a specific task and other stimuli are filtered.[13] Shifting of attention is needed to allocate attentional resources to process information from a stimulus more efficiently. Researches have shown that when there is attention on an object or an area, processing of the information operates more efficiently.[14] When switching attention from a task to another one there is a loss in performance because some effort is put into shifting the attention.[13] Different theories hypothesize how the process of attention shifting might work and how actually does the attention change through space.

2.1.2 Theories of Attention Shifting

One of the theories is the unitary resource model. According to this theory, attention is a single resource that is shared among different tasks. When a task requires a certain amount of attention, individuals voluntarily deliver attention resources to that task.[15] A theory in opposition with the unitary resource model is the theory of multiple resource which states that different attentional resources exist for different sensory and response modalities.[16] The moving-spotlight theory identifies attention as a movable spotlight that is directed towards different targets, one at the time. When a task gets the attention, processing is more efficient since there is an inhibition from any stimuli outside the attended task.[17] Finally, has been proposed that attentions adheres to a gradient theory which states that resources are given to a region in space rather than a single tasks. This also implies that the further from the center an attention point is, the less the resource allocated for it. Attention can rise and fall many times during different fixation times over time. This means that the attention of a future state is dependent on where the previous attention state was directed.[18]

2.2 Overt and Covert Attention

Spatial attention can change with eyes opened or closed. The former case is known as “overt” attention while the latter is defined as “covert attention”.[19] The human eye sharps focus through the fovea. Eyes must continually move in order to direct the fovea to the target. Before moving the eyes to the target overtly, covert attention shifts to this location.[20] Although attention is also able to shift covertly while fixating.

2.2.1 Neurology of Overt and Covert Attention

Neurological studies on patients affected with brain damage were performed to identify the nature of attention shift. Posner et al. [21], studied people with difficulty to move eyes voluntarily.The mid-brain area and associated cortical areas were found to be affected. Other researches indicate differences in brain areas activated for overt attention shifts versus covert shifts. The frontal cortex has been identified has location with high activity, especially the central sulcus. Also the parietal and occipital cortices have been shown activity for overt and covert attention shifts. [22] Many studies used fMRI to show that overt and covert attention activate the same areas (the frontal, parietal and temporal lobes) during task shifting. Result have shown that there is often overlapping of area activated by attention shifting and it has been suggested that overt and covert attention share the same neural mechanisms. Switching from one task to another can happen voluntarily (endogenous control), or automatically(exogenous control). In endogenous control attention is voluntarily directed on the target while exogenous control attentions shifts automatically towards a stimulus.[23]

2.2.2 Neural overlap for Voluntary and Reflexive attention

Although it has been suggested by many studies that multiple areas of the brain are involved in shifts of attention, it appears that no conclusion can be drawn regarding any overlap in activation areas of voluntary versus reflexive attention. A study conducted by Rosen et al. [24] showed overlap between endogenous and exogenous shifts of attention. Activation areas were located in the dorsal and parietal premotor areas. Voluntary attention also showed activation in the right dorsolateral prefrontal cortex. Since it is believed that this area is associated with working memory, it may suggest that working memory is engaged voluntarily. Despite some differences, voluntary and reflexive shift of attention showed consistent overlap in the dorsal premotor region, the frontal eye field area, and the superior parietal cortex.[24] Shift of attention comprehends several neural mechanisms. Despite the difference between the nature of attention shifting it has been shown to be overlapping in neural activation although the magnitude of activation may differ dependently to the attention shift. Resources related to attention may depend on the nature of the attention shift, endogenous versus exogenous. Lastly, attentional shift occurs across modalities and depends on different properties in order to share attention and efficiently process information.

Chapter 3

Brain Computer Interface

3.1 BCI

The goal of BCI technology is to give to severely paralyzed people another way to communicate, a way that does not depend on muscle control.” (Wadswoth Center) Brain Computer Interface (BCI) is a systems capable of acquiring brain signals, analyze them, and translate them into commands that are sent to devices in order to perform desired actions. The main goal of BCI is to replace or restore useful function to people disabled by neuromuscular disorders such as amyotrophic lateral sclerosis, cerebral palsy, stroke, or spinal cord injury. Brain-computer interfaces may also prove useful for rehabilitation after stroke and for other disorders and promising results suggest that BCI might augment performance of professionals in a medical setting. As discussed further in the following chapters, BCI need robust and reliable signal-acquisition hardware that can be easily transported. BCI systems also need paradigms to be validated real use case scenarios, use by people with severe disabilities,under many environmental circumstances.[25]

3.1.1 What is a BCI

According to the Swartz Center for Computational Neuroscience, BCI is a system that takes biosignal measured from a person and predicts (in real time on a single time basis) some abstract aspects of the person’s cognitive state. Cognitive state has different aspects and describe the brain state at a given moment. These aspect must be measurable with sufficient single trial reliability. There are three main cognitive states: tonic, phasic and event related state. In the tonic state it is measured the degree of relaxation. The phasic state helps to determine attention switching. Finally, the event related show cognitive processes related to stimuli given by the external environment.

Figure 3.1: Basic BCI Diagram

There are three main BCI categories:

- Active BCI : Controlled by focus voluntary thoughts.
- Reactive BCI: Controlled by voluntary thoughts but using brain processes that happen in response to external events.
- Passive BCI: Not controlled by thoughts. Any brain process is recorder and it is used to analyse different other parameters. Several passive BCI may run in parallel since they do not require attention on specific tasks.

3.1.2 Modern BCI Design

BCI are made of different systems responsible for input of brain signals, their amplifications and analysis. BCI is a closed loop system in which the analyzed signal is reshaped and shown on an output device accordingly to the end goal. Brain signals are recorded using electroencephalogram (EEG) electrodes which are inexpensive devices that are coupled with a gel solution in order to reduce impedance and thus get a better signal. Other recording devices, less popular than EEG electrodes are microarrays and neurochips which are not biologically sustainable and highly invasive because they have to be implanted on the brain cortex.

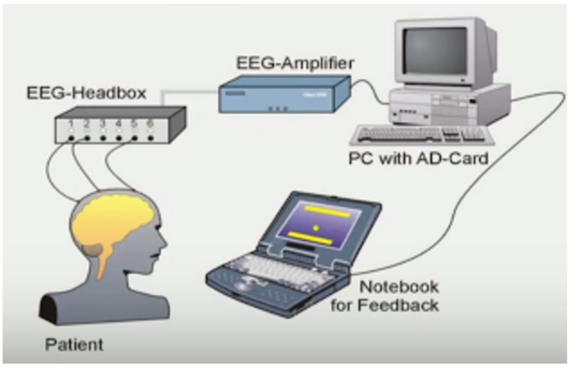

Figure 3.2: Simple BCI Setup

3.1.3 Applications and Examples

The actual traditional population for BCI is made of severely disabled people. There are 2 main condition specifically: locked in Syndrome when a person is not able to move limbs due to neurological disorder. The pathology locks patients in their own body. Communication at this stage becomes crucial. Another condition is tetraplegia in which limbs become unusable. For this special population there is wide use of speller programs which allow to send emails or communicate with the external environment through brain signals sent by the patient to the BCI software. Systems can be active (the patient actively send a signal to reach a goal) or reactive (the patient reacts to the stimulus offered by the BCI program).

Beside communication, BCI is also helpful in prosthetic control and wheel chair control. Finally, BCI is applied in environmental control in smart house integrated systems.

Outside healthcare, BCI find a spot in drive safety (road danger or fatigue). Other BCI system help to improve performance in jobs where attention is critical.

3.1.4 Scientific Challenge

From a scientific point of view is not a trivial topic because it entails many different disciplines in from engineering and medicine fields such as signal processing, machine learning, neuroscience, cognitive science and physics. Processing of information depends on parameters that are unknown a priori thus increasing complexity of designing a paradigm. Parameters are person-specific, task specific or specific to other aspects. Between subjects there is an high degree of variability due in primis to biological/anatomical reasons. To state an example, the folding of the brain cortex differs between people and thus relevant functional map differ across individuals. Furthermore, brain dynamics are non-stationary at all time scales. Experimental setting may also make a difference in measurements since the position of the sensors might actually differ within the same subject if for example EEG cap is replaced during the experimental session. Sensitive measures are difficult to obtain since relevant brain activities are small compared to artifacts and background activities of the brain, it is therefore difficult to isolate the target signal. Giving the ability of neurons to be used for different activities, it is difficult to isolate the effect of a specific phenomenon. Finally, the physiology of the brain is not fully understood and this has an effect of the paradigm performance. All the above listed challenges require the use of statistical approaches to cope with uncertainty as well as sophisticated signal processing techniques. BCI systems must be calibrated before they can be used. Calibration should be made with the highest amount of information possible in order to widen the a priori knowledge.

3.1.5 Attention Shifting in BCI

When working with BCI in experimental settings, most of the studies have been performed with very little noise and distractors. Although a real-life scenario is different since in a hospital noise and distraction are present and furthermore subject get fatigued.[26][27] When a BCI is designed for neuro-rehabilitation, a correct and reliable detection of movement (or movement intention) plays a key role for the activation of the output device.[28] Studies have shown that whenever the attention of a user shifts from the main task, the accuracy in detecting the movement intention may be lower [29] [30]

Chapter 4

Electroencephalogram

4.1 EEG

There are a lot of electrical processes in the brain since thousands of neurons fire and produce an electric field. EEG, in fact, reads electrical signals from these firings coming from a large population of neurons firing in synchrony. The main contribution of the firing signal is given by pyramidal cells which are positioned radially to the brain cortex, thus, when they fire, their electrical contribution adds up. This would not happen if neurons were positioned parallelly to the cortex.

4.1.1 Event Related Potential

Event related potential (ERP) are defined as tiny voltages generated in the brain and they are generated as a reaction of certain stimuli.[31] ERP can be triggered by several different events such as sensory, motor and cognitive stimuli. They have been physically associated to the synchronous firing of thousands (or even more) neurons when stimuli are processed.[32] ERP are classified into two main categories depending on the their reaction time to the onset of a stimulus. ERP that peak around 100ms after onset of the stimulus are defined sensory (or exogenous) ERP since their peak depends on the stimulus. ERP generated in a longer timeframe are defined as cognitive (or endogenous ERP) and they are related to the interpretation of the stimulus at higher levels. There are different types of ERP waveforms and they are described depending on latency and amplitude. For sake of simplicity, only Movement Related Cortical Potential (MRCP) will be discussed.

4.1.2 Movemement Related Cortical Potential

Movement Related Cortical Potential (MRCP) is a negative shift shown in the EEG and it's triggered around 2 seconds prior onset of a voluntary movement and are referred to the readiness of a movement. MRCP can be generated in relation to planning and execution of a movement and takes the name of Contingent Negative Variation (CNV) while if it is triggered as response for self-paced movement it is defined as Bereitschafts Potential (BP). CNV originates between 2 and 1.5s, right in between the "Focus" and "Move!" stimulus.[33].

It describes the readiness to act in response to a stimulus and it is thought to be related to the anticipatory process. The early CNV is a response to the “Focus” signal and is maximally present in the frontal cortex while later CNV starts around 1.5s before the “Move!” and has maximal amplitude in the motor cortex. (C. H. M. Brunia, 2003) BP is defined as negative cortical potential triggered between 1.5 and 1s prior the onset of a voluntary movement. [34]. It is mainly divided into two parts, a slow rising negative called “early BP” which is developed 1.5s prior the movement onset, and a second part defined as “late BP”, characterized by a steeper slope developed 500ms before movement onset. MRCP also comprises other two potentials defined as Motor Potential and Movement-Monitoring Potential (MMP), which express movement execution and control of performance.[35] MRCP has been evaluated as rehabilitation technique for supporting motor in healthy subjects as well as patients with different pathologies such as Amyotrophic Lateral Sclerosis, tremor, Parkinson’s disease and stroke.[36] MRCPs associated with imaginary tasks have been suggested being useful for rehabilitation practice when the movement can be imagined.[37]

4.1.3 Spatial Characteristic of EEG

Spatial characteristics depend on brain anatomy. As discussed in the physiology chapter, different parts of the brain react differently to stimuli of different nature. It is always advisable to constrain the area of EEG analysis in order to pick up the best signal reducing the noise coming from other areas which are not of interest. The brain cortex is associated with defined areas of the body, this functional mapping is expressed using the concept of “Homunculus”. In relation to the signal, a special attention has to be put on the source of the EEG. From the neuron to the EEG electrode, there is a thick volume conductor made of skin, skull and hair and furthermore the disposition of the neurons related to the cortex has its importance. Due to the volume conductor, the energy coming from the neurons and read by the electrodes is highly attenuated. Electrode placement follows the standardized location system called “10-20” system which was created to ensure that positions are universally labeled. The system names the positions with a letter which expresses the position (i.e. frontal or central) and a number which expresses whether the electrode lies on the right (even number) or left hemisphere (odd number) while the central position is expressed using the letter “z”.

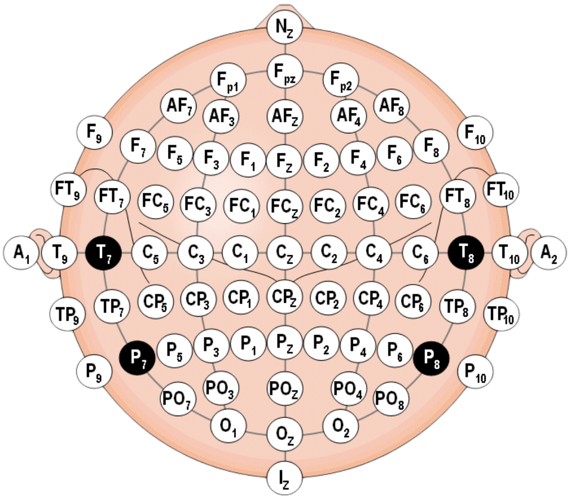

Figure 4.1: 10-20 Electrode Disposition

4.1.4 Temporal Characteristics of EEG

Normally a neuron has a spiking behavior that matches the reported picture. Of course the representation do not report only the spiking of a single neuron but instead the merged spiking of thousands of them. EEG is filled with oscillatory processes such as the brain waves described above in the brain waves section.

4.1.5 Artifacts

A artifact is anything that it is artificially introduced in EEG signal. Normally larger in amplitude than EEG activity signal since they are made from i.e. big skeletal muscles instead of small neurones. Artifacts may be internally generated, externally generated or sensor related. Internally generated artifacts are generated in muscles located in the neck, face, eyes and heart. Externally generated artifacts are noise with frequency between the 50-60 Hz interval and it is related to the equipment. Finally, as the name suggests, sensor related sensors are due to sensors components such as thermal (surface electrode-skin) and quantization noise.

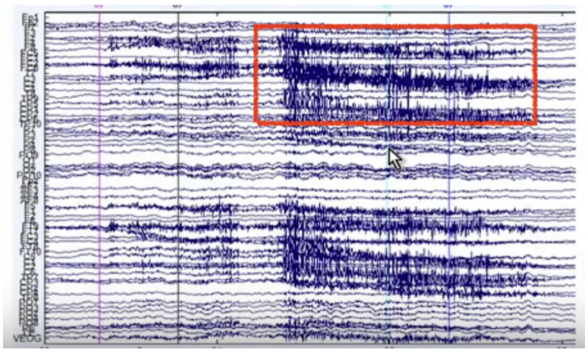

Figure 4.2: Example of muscle artifact

Eye blinks are signal characterized with large-low frequency peaks present mainly in frontal channels.

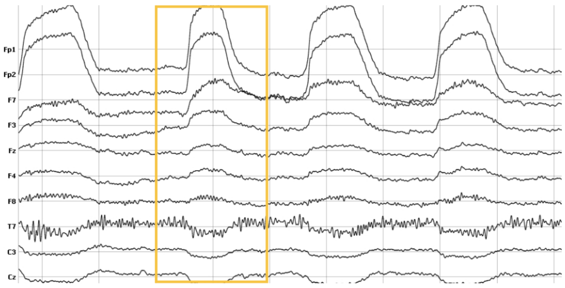

Figure 4.3: Example of blinking artifact

4.1.6 EEG Acquisition

EEG systems use electrodes attached to the scalp to pick up electric potentials generated by neurons in the brain. The electrode gel placed between the electrode and the skin functions as capacitor and attenuates impedance. Commonly electrodes are made of silver but alternatively on the market are present dry EEG electrodes which make direct contact with the skin and thus do not require gel. Dry electrodes more convenient to apply, but are more prone to artifacts.[38] The number and placement of electrodes depends on existing results and findings, F.e. A pilot experiment is carried out before deciding the final placement of the electrodes. MRI recordings might be useful in situations where experimenters have no or little information about the process to analyse. In EEG, the amplitude of the potential is measured as difference between a chosen electrode and the ground electrode and the potential between the reference and ground electrodes. Typical reference sites are the tip of the nose and ears.

4.1.7 Signal Processing in EEG

As previously mentioned, BCI is a mix of many different technical topics and it can be seen differently depending on the used approach. In this section, signal processing techniques are shown. Signal processing consists in taking a source signal as input, filter it and transform it into another signal. A signal can be thought as a mapping from an index set into vector. A BCI transduces the input signal x(n) into a control signal y(n). This translation is called transformation:

$$y(n) = T[x(n)] \tag{4.1}$$

A system is defined as static if the value y(n)depends only on x(n)at any sample, the system is otherwise defined as dynamic. A system is called causal if the output y(n) depends only on x(m)for m n, at any time. The system is otherwise defined non-causal. A system is called time-invariant if y(n)=T[x(n)] with y(n-k) =T[x(n-k)] for every time k. Otherwise the system is called time-variant. Finally, a system is linear if the equation T[a1x1(n)+a2xa(n)]is verified for every input x1(n)and x2(n). Otherwise the system is defined nonlinear. BCI operates in real time, they are therefore causal systems. Since temporal filter is performed in BCI systems it can be said that BCI are dynamic. Normally BCI are not linear systems. The major category of filters are static, spatial, temporal and spectral filters. Static filters are normally used for signal squaring in which a static system takes an input signal and the filter calculates the variance of it. Spatial filters operate across space. They convert a multi channel input signal in a multichannel output signal. Spatial filters are important is BCI due to the fact that the volume conductor around the signal source (the brain) is a linear mapping. This assumption means that the mapping from the source to the sensor is linear and it is therefore possible to establish the original signal at the source, starting from the signal measured at the sensor. This allows to operate at the source level where signal is more precise instead of sensor level where the signal is distorted by the volume conductor. An example of spatial filter is the Surface Laplacian which is used for several purposes in BCI research such as reducing spatial noise[39], constraining the potential source of the signal [40] and has been shown to improve spatial resolution [41] which can be helpful in source identification. Temporal filters transfer information across time. Temporal filters generate an output signal on a channel that is dependent only on the same channel in a previous moment in time. Temporal filters don't process spatially across channels but only across time. One of the most common temporal filters is the wavelet. The wavelet transform is a trade off between spatial filtering and temporal filtering. Normal spatial filtering identifies the frequencies in a certain location but the temporal feature is lost. Temporal filters are accurate to describe when a frequency happens but omit the spatial feature. Wavelet filter is not constant, it starts with analysing a small size window which will be highly accurate in defining the temporal feature but it will identify only high frequencies.After the window has analysed the whole signal, the identified frequencies are removed from the original signal. The process iterates defining an analysis window which, at each step, is double in size compared to the previous ones. Bigger analysis window allow to retrieve lower frequencies with less time accuracy. Finally, spectral filter are temporal filter designed for their effect on the spectrum of the signal. Examples of spectral filters are low pass, high pass, bandpass and notch filters and the main use in BCI is to isolate the ERP of interest. Any of the aforementioned filters has a specific order which represents how many times will be the filter repetitively applied on the source signal. To affect low frequencies the order must be high (large filter) while for affecting high frequencies the order must be low (narrow filter).

4.1.8 Machine Learning

BCI systems use machine learning to understand and describe brain processes. Machine Learning is based on trials and it is based on two main function, the supervised learning function and the prediction function. The learning function takes as input some data which is already labelled (a priori knowledge) and releases a model as output. This model will be used for classifying new unlabelled data. Machine learning is needed in BCI due to the high subject-to-subject variability or session-to-session variability that would necessitate the system to be re-adapted for each session and for every user. Reference on the machine learning approach used in the project can be found from section 5.1 onward.

Chapter 5

Methodology

5.1 Experiment Basis

The objective of this section is to provide a common ground and understanding of the basis of this work, including subject's criteria, signal acquisition and the studied tasks. The described methodology below was applied throughout the study.

5.1.1 Participants

The inclusion criteria for the experiment were healthy subjects, with no neurological conditions nor auditory deficiencies, between the age range of 20-30 years old.

5.1.2 Signal Acquisition

EEG signals were recorded from AF4, FC3, FC4, C3, Cz, C2, C4, CP2, P3, P1, Pz and P2 locations, according to the standard international 10–20 system. Reference electrode was assigned to Fp1, and the ground electrode was placed on the left earlobe. EEG active electrodes (g. GAMMAcap2, Austria) were used for the acquisition. EMG signals were obtained using two monopolar surface gelled electrodes (Ambu Neuroline 720), placed at the right tibialis anterior (TA), to monitor subject's movement. All signals were recorded with g.USBamp amplifier (gTec, GmbH, Austria), and sampled at 256 Hz (16 bits accuracy).

Force during dorsiflexion was recorded with pedal sensors and FollowMe LabView software, using track mode configuration in a 300 s hold time.

5.1.3 BCI Tasks

As previously mentioned, the aim of this study was to evaluate the effect of feedback in a BCI with attention variation. This attention difference implies two phases: one where the subject is focused in the main task, and another one where subject's attention is diverged between the main task and an additional secondary task.

During the experiment, subjects were asked to sit with their knees in a ninety-degree angle, and their feet resting on facing pedals. A digital screen was in front of the subjects at a one-meter distance to show the visual cue (see Figure 5.1) [42].

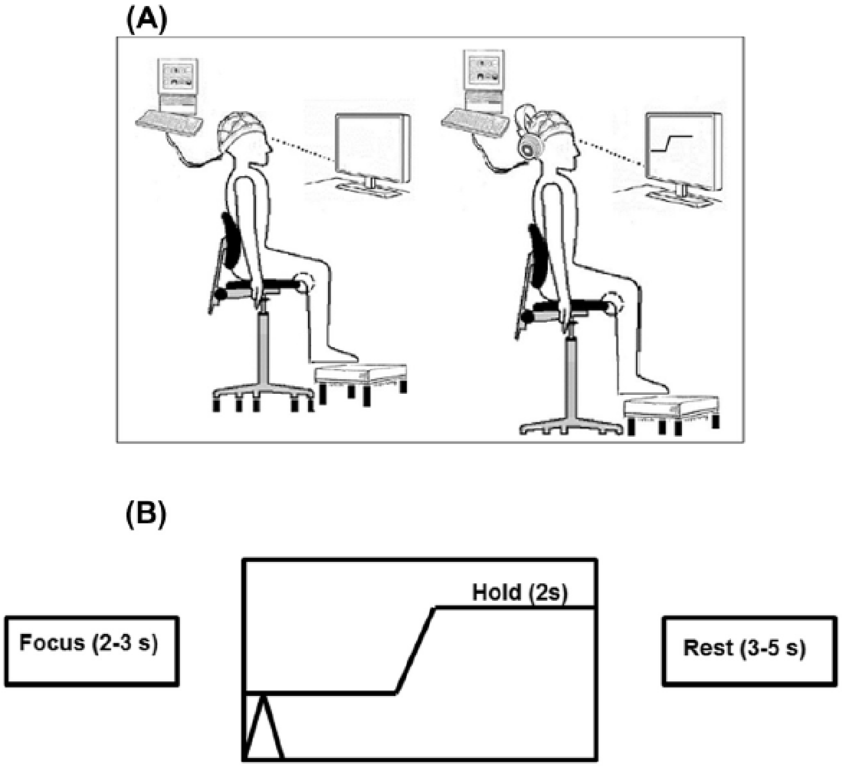

Figure 5.1: BCI setup based on [42]. Subfigure A shows the position of the subject and screen. Subfigure B depicts the phases and shape of the movement cue.

Main task: Motor movement

In this BCI configuration, the main task was cue-based dorsiflexion. The cue was visually presented to guide the subjects during the movement performance. It included five stages: Focus, Preparation, Execution, Hold and Rest. Focus and Rest phases were indicated with the corresponding text displayed on the screen for a randomized time (between 2-3 s and 3-5 s, each). Preparation, Execution and Hold were mapped to a ramp function – low state, increasing slope and high state, respectively (see Figure 5.1) [42]. A moving cursor determined the change of phase in the ramp. Subjects had to sustain dorsiflexion during the hold state, which lasted 2 s.

Secondary Task: Auditory Oddball

To divert the attention of the participants, four tones, at frequencies: 700, 1200, 1700 and 2200 Hz with 0.5 s duration, were played during the main task. Both the order and timing of the tones were randomized. Conventional headphones were used to play the sounds, and loudness was adjusted for each participant.

Subjects were presented all tones twice at the beginning of each paradigm, and were requested to count a specific two-tone sequence throughout the experiment. To encourage sequence counting, subjects were randomly asked the number of sequences during the experiment.

5.2 Pilot Studies: Experiment Optimisation

Several pilot studies were required to determine which processing analysis and paradigm configuration was optimal to distinguish between focused and attention diversion trials.

5.2.1 PILOT I: Feature and Classifier Optimisation

Participants

Two healthy subjects (1 male and 1 female, mean age 25 years old), participated in this pilot complying with the ethical agreement and inclusion criteria.

Signal Acquisition

Signal recordings were acquired as described before, during two sessions: one for focus (control) and one for attention diversion (attention). These sessions were separated by 5 min to allow the subjects to rest.In the control session, subjects were just asked to perform the main task, whereas in the attention session, both tasks were required. Both sessions were composed of 30 dorsiflexion repetitions.

Signal Processing

All signal processing was carried out in MATLAB. Firstly, EMG signals were analyzed to detect movement onsets. EMG signals were normalized and digitally filtered with a 4th order Butterworth bandpass filter between 20-500Hz [43]. Samples corresponding to the first second of the EMG signals, were set to the baseline value due to an artifact produced by the automatic gain calibration of the amplifier. The power of the signal was calculated, and inputted into a moving average smoothing operator (five-sample window span) to obtain the envelope. Thresholds for movement onset were manually set for each subject and session, based on these power envelopes.

The obtained movement onsets were used to extract the temporal and spectral features of the classifier. MRCPs were computed by digitally filtering each EEG channel with a

2nd order Butterworth bandpass filter from 0.5-3 Hz in the [-3,3] s window, centered at the movement onset [44, 45]. Twenty temporal features were extracted from the MRCP, including: Value Peak Negativity(VPN), Time Peak Negativity (TPN) and the mean slope and variance over six time intervals ([-2,0], [-2, -1], [-1, 0], [-1, -0.5], [-0.5,0], [0, 1]). According to [44], attention variations produce significant changes in the MRCP features in these windows.

Thirty spectral features were extracted for each channel. The mean power of the delta, theta, alpha, beta and gamma brain waves was also computed for the six time windows mentioned before. EEG channels were digitally filtered by a 4th order Butterworth bandpass filter from: 0.05-3 Hz (delta), 4-7 Hz (theta), 8-13 Hz (alpha), 16-31 Hz (beta), 32-100 (gamma), to obtain the frequency bands.

MATLAB Classification Learner was employed to test features' robustness and to identify the optimal classifier. Classifiers were designed to be channel specific to localize the areas more affected by shifts in attention, and reduce the number of channels in the future. For this reason, neither dimensionality reduction nor spatial filtering were applied. Therefore, for each channel, the temporal feature set, spectral feature set and the combination of both, were evaluated using all fast-training MATLAB classifiers (Simple Tree, Medium Tree, Complex Tree, Linear Discriminant, Quadratic Discriminant, Logistic Regression, Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM, Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN, Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN and RUSBoost Trees). Five-fold validation was applied to calculate the accuracy of the classifier, defined as the percentage of correctly classified samples over the total number of samples.

For each channel and feature set, maximum classification accuracy and used classifier were stored. Classification accuracies of the three feature sets were compared within subjects to select the optimal one. Similarities between the best performant channels and classifiers were of special interest for next experiments.

Statistics

Repeated Measures ANOVA was used to evaluate the differences in classification accuracy (dependent variable) generated by the three feature sets (within-subjects factor) for each subject. Normality of the data was confirmed by Shapiro-Wilk test. Results were considered significant for $p \leq 0.05$.

5.2.2 PILOT II: Paradigm Optimisation

The results of the previous pilot study were used to design the first main experiment paradigm (pilot II). The aim of this pilot was to evaluate the designed paradigm's efficiency, to assess the effect of visual feedback in subject's attention.

Participants

Seven healthy subjects (3 males and 4 females, mean age 26 years old), participated in this pilot complying with the ethical agreement. Participants were divided into two groups: one for testing without feedback (WOfeed) and the other one with feedback (WITHfeed). Both groups were balanced and subjects were randomly assigned to each one (4 in WOfeed and 3 in WITHfeed).

Signal Acquisition

Signal recordings were acquired according to the Experiment Basis section. However, the setup of this experiment was more complex than the previous pilot. To assess the effect of feedback a training and testing paradigms were required.

During the training phase, control and attention sessions were separately recorded for 30 dorsiflexion repetitions each, as described in Pilot I. On the other hand, in the testing stage, both trials were randomly intercalated for 60 dorsiflexion repetitions. The probabilities of attention and control trials were 60% and 40%, respectively. WOfeed group was provided the same visual cue as in training. However, for WITHfeed participants, the BCI screen was horizontally divided to show the cue and the feedback. A colored rectangle was displayed during the Rest phase to give subjects feedback about their performance. Green meant control (focus state), whereas red stood for attention (unfocused) trials. Subjects were encouraged to focus more on the next dorsiflexion movement, if a red rectangle appeared.

Signal Processing

Calibration of the training paradigm
Firstly, the system was calibrated after acquiring the control and attention sessions. Based on the results of Pilot 1, only the spectral features were extracted for each channel. In this calibration phase, movement onsets were calculated based on the EMG signals. Ten-fold validation was applied to the obtained spectral features to divide the data into training and testing subsets, following a ratio of 9:1. This data was fed to the two classifiers with highest accuracy in Pilot 1 (Trees and SVM). The classification error (CE), defined as the percentage of misclassified samples, was subsequently computed. For each channel, only the classifier with lower CE was considered. The five channels with lowest CE were selected for majority voting in the online testing paradigm (WOfeed/ WITHfeed). Therefore, their corresponding trained classifiers were stored and parallelly evaluated in the next paradigm.

Performance analysis of the testing paradigm
To compare the attention level of WOfeed and WITHfeed groups, the True Positive Rate (TPR), True Negative Rate (TNR) and accuracy were calculated based on the results of the majority voted classification. TPR was defined as the number of attention (unfocused) trials that were classified correctly, whereas, TNR represented the number of control (focused) trials classified correctly. Accuracy was calculated as the sum of the correctly classified samples

divided by the total number of samples.

In order to assess similarities between subjects, the selected channels for majority voting were also compared.

Statistics

Mixed ANOVA was applied to see the interaction in accuracy (dependent variable) between calibration and online (within-subjects factor), and the WOfeed and WITHfeed paradigms (between-subjects factor). T-test was used to evaluate the TNR between the WOfeed and WITHfeed independent groups. Normality of the data was confirmed with Shapiro-Wilk test. Results were consider significant for $p =\leq 0.05$

5.3 Main Experiment

The optimisations of the pilots, were used to refine the setup and paradigms of the main experiment. The goal of this main experiment is to evaluate the effect of feedback in a BCI with attention variations.

5.3.1 Participants

Eleven subjects (5 males and 6 females, mean age 25 years old) took part in this study in accordance with the ethical agreement and inclusion criteria. Based on the results of Pilot 2, the parallel study structure was changed into a crossover study. Therefore, all subjects performed both the WOfeed and WITHfeed. However, the order of these training sessions was randomised and balanced (6 for WOfeed/ WITHfeed and 5 for WITHfeed/ WOfeed). Two subjects from the same subgroup were discarded due to the high number of artifacts in the signals.

5.3.2 Signal Acquisition

Signals were recorded following 5.1 . The low correlation between the offline training and online testing classification accuracy, suggested that separated sessions of the control and attention trials, do not provide a robust training for the online paradigm where both focus and unfocused states are alternated. For this reason, the training paradigm was modified to a single session of randomly alternated control and attention trials, with equal probabilities (50%) during 50 dorsiflexion repetitions.

To maximise the similarity between the training and the testing, WOfeed and WITHfeed sessions were also changed to 50 dorsiflexion repetitions with equally probable attention states. Cue and feedback display remained the same. Subjects had ten-minute breaks between sessions to minimise fatigue.

5.3.3 Signal Processing

acquired signals were processed as described in Section **??**. The mean power of the delta, theta, alpha, beta and gamma waves was calculated for six time windows ([-2,0], [-2, -1], [-1, 0], [-1, -0.5], [-0.5,0], [0, 1]) centred at the movement onset. In this case, movement onset calculation was based on the cue during calibration to enhance reproducibility between paradigms. Channel-specific Trees and SVM classifiers were trained using ten-fold validation. The classifiers of the five channels with lowest classification error, were used during the online testing (WOfeed/WITHfeed). The outputted class was calculated as the majority voting of the parallel classification. A categorical analysis of the selected channels for all subjects was carried out to assess similarities among the most attention-affected regions.

To evaluate the online testing, TNR, TPR and Accuracy were computed for both WOfeed and WITHfeed as explained in Section **??**. We hypothesised that feedback would increase subjects' concentration, increasing the false negative rate (attention trials classified as control), and thus, decreasing the TPR with respect to the WOfeed session.

5.3.4 Statistics

Two repeated measures ANOVA test was employed to study the effect of the feedback paradigms (within-subjects factor) in TPR and TNR (dependent variables). In addition, changes in classification accuracy (dependent variable) were also evaluated with a repeated measures ANOVA, for the offline calibration an the testing paradigms (within-subjects factor). Shapiro-Wilk tests was used to check the normality of the data. Results were considered significant for $p \leq 0.05$.

Chapter 6

Results

6.1 PILOT I: Feature and Classifier Optimization

The results given in Table 6.1 and Table 6.2 show the maximum classification accuracy for each subjects' channel, with the employed classifier and feature set. In some cases, maximum accuracies were reached with more than one classifier.

Repeated measures ANOVA showed significant interaction between subjects and feature sets ($p = 1.3 \times 10^{-5}$). The Bonferroni pairwise comparison determined that temporal features produced significantly lower classification accuracy than spectral ($p = 6.14 \times 10^{-10}$) and the combination of all ($p = 2.3 \times 10^{-3}$). On the other hand, no significant improvement in accuracy was found using all features instead of just the spectral set ($p = 0.103$). Finally, the overall performance of the subjects was revealed to be significantly different ($p = 0.021$).

To better observe these performance differences, Figure 6.1 depicts the boxplot of each feature set for each subjects. The median of the maximum classification accuracy for the temporal features, is the lowest in both subjects. The combination of all features showed the highest median accuracy for subject 1, but was surpassed by the spectral feature set in subject 2.

Considering that computing all features did not significantly improve the classification accuracy, spectral features were selected for the next studies. A categorical analysis of the maximum accuracy generated by the spectral features, indicated that the most repeated classifiers were variants of Trees and SVM (see Figure 6.2).

6.2 PILOT II: Paradigm Optimisation

The channels given in Table 6.3, represent the optimal channels (highest accuracy) for detecting attention variations. The most repeated ones are: FC3 (in 5/7 subjects), FC4 (in

Channels	Max. Acc. (Temp. Feat)	Classifier (Temp. Feat)	Max. Acc. (Spec. Feat)	Classifier (Spec. Feat)	Max. Acc. (All Feat)	Classifier (All Feat)
AF4	68.30%	Med. Gauss SVM	71.70%	Med. Gauss SVM	70.00%	Quadratic SVM
C2	73.30%	Cosine KNN	68.30%	Cubic SVM/ Weighted KNN	66.70%	Logistic Regression
C3	66.70%	Med. Gauss SVM/ Cosine KNN/ Bagged trees	70.00%	Cubic SVM	65.00%	Cosine KNN
C4	75.00%	Quadratic SVM	70.00%	Cosine KNN/ Bagged Trees	66.70%	Quadratic SVM/ Med. Gauss SVM
Cz	68.30%	Quadratic SVM/ Cubic SVM	68.30%	Weighted KNN	71.70%	Med. Gauss SVM/Cosine KNN/ Cubic KNN
CP2	58.30%	Med. Gauss SVM	73.30%	Med. Gauss SVM/ Bagged Trees	66.70%	Quadratic SVM
FC3	68.30%	Medium KNN	70.00%	Cubic SVM	71.70%	Med. Gauss SVM/ Weighted KNN
FC4	63.30%	Coarse Gauss SVM	66.70%	Bagged Trees	70.00%	Bagged trees
P1	68.30%	Logistic Regresion/ Quadratic SVM/ Cosine KNN	71.70%	Cubic KNN	73.30%	Cosine KNN
P2	68.30%	Subspace KNN	71.70%	Bagged Trees	75.00%	Fine KNN
P3	61.70%	Complex tree/ Medium tree/ Simple tree/ Quadratic SVM	70.00%	Cubic KNN/ Bagged Trees	73.30%	Med. Gauss SVM
Pz	65.00%	Cosine KNN	68.30%	Med. Gauss SVM/ Bagged Trees	73.30%	Medium KNN

Table 6.1: (Pilot 1) Feature set and classifier analysis of subject 1

SUBJECT 2						
Channels	**Max. Acc. (Temp. Feat)**	**Classifier (Temp. Feat)**	**Max. Acc. (Spec. Feat)**	**Classifier (Spec. Feat)**	**Max. Acc. (All Feat)**	**Classifier (All Feat)**
AF4	53.30%	Logistic Regression	80.00%	Bagged Trees	58.30%	Medium KNN
C2	63.30%	Subspace Discriminant	85.50%	Bagged Trees	63.30%	Logitic Regression
C3	60.00%	Subspace Discriminant	86.70%	Complex Tree/ Medium Tree/ Simple Tree	53.30%	Subspace Discriminant
C4	60.00%	Logistic Regression	90.00%	Complex Tree/ Medium Tree/ Simple Tree	56.70%	LDA
Cz	65.50%	Subspace Discriminant	78.30%	Complex Tree/ Medium Tree/ Simple Tree/ Bagged Trees	78.30%	Coarse Gauss SVM/ Bagged Trees
CP2	63.30%	Subspace Discriminant	81.70%	Complex Tree/ Medium Tree/ Simple Tree/ Bagged Trees	68.30%	Subspace Discriminant
FC3	56.70%	Subspace Discriminant	83.30%	Complex Tree/ Medium Tree/ Simple Tree/ Bagged Trees	80.00%	Complex Tree/ Medium Tree/ Simple Tree/ Linear SVM
FC4	58.30%	Subspace Discriminant	83.30%	Complex Tree/ Medium Tree/ Simple Tree	86.70%	Bagged Trees
P1	53.30%	Subspace Discriminant	86.70%	Complex Tree/ Medium Tree/ Simple Tree	85.00%	Bagged Trees
P2	63.30%	Subspace Discriminant	80.00%	Bagged Trees	80.00%	Linear SVM
P3	63.30%	Subspace Discriminant	83.30%	Bagged Trees	88.30%	Complex Tree/ Medium Tree/ Simple Tree
Pz	66.70%	Subspace Discriminant	83.30%	Bagged Trees	85.00%	Bagged Trees

Table 6.2: (Pilot 1) Feature set and classifier analysis of subject 2

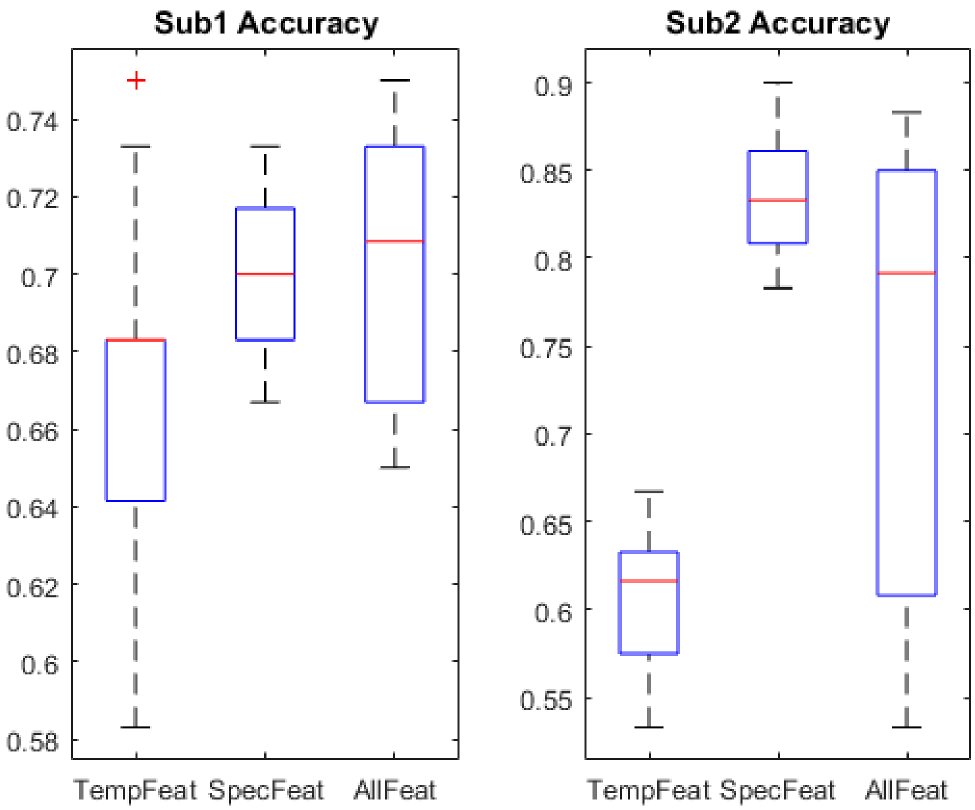

Figure 6.1: (Pilot 1) Boxplot of the maximum classification accuracies for each subjects' channels. Blue boxes represent the interquartile range, dotted black lines the lower and upper limits of the data, and red asterisk outliers in the distribution.

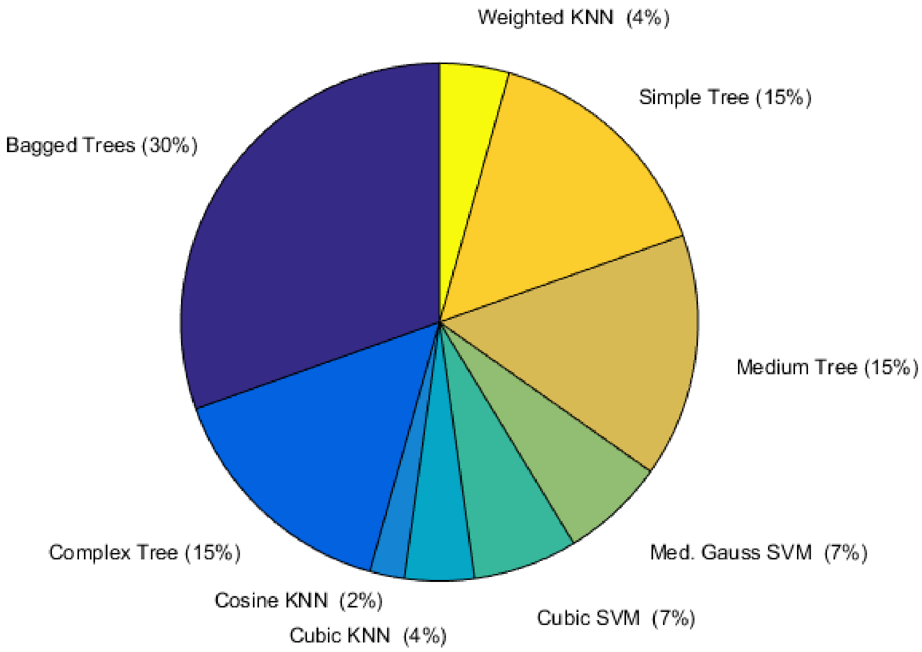

Figure 6.2: (Pilot 1) Categorical analysis of the number of appearances of each classifier in the maximum accuracy table for each subjects' channels. Note that the number of appearances separated the channels with multiple classifiers into several instances.

WOfeed subjects	Ch1	Ch2	Ch3	Ch4	Ch5
sub 1	CP2	P2	FC4	Cz	C2
sub 2	AF4	C2	CP2	P2	FC3
sub 4	P1	FC3	P2	Cz	AF4
sub 6	AF4	FC3	C4	FC4	CP2
WITHfeed subjects	**Ch1**	**Ch2**	**Ch3**	**Ch4**	**Ch5**
sub 3	Pz	C3	P1	P3	FC4
sub 5	Pz	C3	P3	FC3	P1
sub 7	FC4	P2	C3	C2	FC3

Table 6.3: (Pilot 2) Channels with lowest CE in calibration, for WOfeed and WITHfeed subjects

4/7 subjects) and P2 (in 4/7 subjects).

In this experiment, Tree classifier was primarily selected for all subjects' channels (97.14%), just one SVM classifier was selected for the fifth optimal channel.

WOfeed subjects	ACC. (Ch1)	ACC. (Ch2)	ACC. (Ch3)	ACC. (Ch4)	ACC. (Ch5)	Mean ± STD
sub 1	100.00%	100.00%	98.33%	98.33%	96.67%	98.67 ± 1.39 %
sub 2	80.33%	75.41%	75.41%	72.13%	70.49%	74.75 ± 3.77 %
sub 4	75.00%	65.00%	63.33%	58.33%	56.67%	63.67 ± 7.21 %
sub 6	96.67%	91.67%	88.33%	86.67%	86.67%	90.00 ± 4.25 %
WITHfeed subjects						
sub 3	98.33%	96.67%	96.67%	95.00%	78.33%	93.00 ± 8.28 %
sub 5	95.00%	90.00%	90.00%	88.33%	88.33%	90.33 ± 2.74 %
sub 7	93.33%	76.67%	71.67%	71.67%	70.00%	76.67 ± 9.65 %

Table 6.4: (Pilot2) Training classification accuracy of the five optimal channels for each subject

The accuracies displayed in Table 6.4, correspond to the optimal channels selected for majority voting during calibration (see Table 6.3). Table 6.5 show the TPR, TNR and accuracy of the WOfeed and WITHfeed testing paradigms, respectively.

The mean TPR for WITHfeed's subjects was 43.51%, less than WOfeed's subjects, which was 56.94%. On the contrary, in the WITHfeed session, the mean TNR increased 51.39%, with respect to the 46.43% of the WOfeed average. Two independent T-test determined that there was no significant effect between TPR and TNR when comparing WOfeed and WITH-

WOfeed subjects	TPR	TNR	ACC
sub 1	59.52%	32.14%	45.83%
sub 2	73.81%	28.57%	51.19%
sub 4	44.44%	66.67%	55.56%
sub 6	50.00%	58.33%	54.17%
WITHfeed subjects	**TPR**	**TNR**	**ACC**
sub 3	25.00%	87.50%	56.25%
sub 5	58.33%	20.83%	39.58%
sub 7	47.22%	45.83%	46.53%

Table 6.5: (Pilot 2) Performance of the WOfeed and WITHfeed groups

feed paradigms ($p = 0.284$ and $p = 0.812$, repsectively).Although these changes follow the hypothesis that feedback improves subjects' concentration in dorsiflexion, they were found non significant.

The mixed ANOVA test found no significant interaction between training/testing stages and the WOfeed/WITHfeed paradigms in the classification accuracy ($p = 0.492$). Therefore, both factors can be treated as independent variables, meaning that the decrease in classification accuracy from calibration to the online testing, affects both WOfeed and WITHfeed similarly. This accuracy reduction was found significant for both groups ($p = 0.002$), and no significant accuracy differences were found between neither calibration nor testing for WOfeed and WITHfeed ($p = 0.95$).

An average 34.65% less in the percentage of accuracy was obtained when comparing training and testing performances. The main difference between the two phases was the presentation of control and attention trials (in different sessions during training and alternated in testing). Therefore, to optimise the BCI setup to better scope feedback effects, the training paradigm of the main experiment was modified so that it matched the online testing.

6.3 Main Experiment

An analysis of the most selected channels for majority voting was carried out during calibration (see Table 6.6). The categorical analysis concluded that the channels more influenced by attention variations were P2 (in 6/9 subjects), CP2 (in 5/9 subjects), FC3 (in 5/9 subjects) and Pz (in 5/9 subjects).

The corresponding classification accuracies of the five optimal channels are given in Table 6.7 for each subject. Mean accuracy and standard deviation are also included. Tree

	Ch1	**Ch2**	**Ch3**	**Ch4**	**Ch5**
sub 1	P2	C4	CP2	P1	AF4
sub 2	C2	Pz	P2	Cz	AF4
sub 3	P2	C4	C3	Pz	FC4
sub 4	C4	FC4	AF4	Cz	CP2
sub 5	FC3	FC4	P1	CP2	Pz
sub 6	P2	CP2	FC3	C2	Pz
sub 7	AF4	C3	FC3	P1	Pz
sub 8	C2	FC3	Cz	P2	CP2
sub 9	FC3	C4	Cz	P2	P3

Table 6.6: Selected channels for online majority voting based on the lowest CE during calibration.

classifier was again more used (78%) than SVM (27%).

	ACC. (Ch1)	**ACC. (Ch2)**	**ACC. (Ch3)**	**ACC. (Ch4)**	**ACC. (Ch5)**	**Mean ± STD**
sub 1	70.00%	62.00%	60.00%	58.00%	56.00%	61.20 ± 5.40%
sub 2	78.00%	66.00%	64.00%	62.00%	58.00%	65.60 ± 7.54%
sub 3	60.00%	58.00%	54.00%	54.00%	53.33%	55.87 ± 2.96%
sub 4	80.00%	58.00%	56.00%	56.00%	54.00%	60.80 ± 10.83%
sub 5	74.00%	72.00%	70.00%	64.00%	64.00%	68.80 ± 4.60%
sub 6	64.00%	62.00%	58.00%	56.00%	56.00%	59.20 ± 3.63%
sub 7	70.00%	68.00%	58.00%	58.00%	58.00%	62.40 ± 6.07%
sub 8	84.00%	78.00%	66.00%	66.00%	64.00%	71.60 ± 8.88%
sub 9	58.00%	56.00%	54.00%	54.00%	52.00%	54.80 ± 2.28%

Table 6.7: Individual classification accuracy of the five optimal channels of each subject

The performance of the online testing paradigm is shown in Table 6.8 in terms of Accuracy, TPR and TNR for each WOfeed and WITHfeed session.

To provide a frame of reference of the accuracy of the BCI system, the changes in classification accuracy for the offline calibration, WOfeed and WITHfeed paradigms were evaluated by a repeated measures ANOVA (see Figure 6.3). Results showed significant differences between the paradigms ($p = 0.028$), so Bonferroni pairwise comparison was applied to identify the specific significant effects. The general decrease in accuracy from calibration to the WOfeed was determined to be significant ($p = 0.028$). In contrast no significant changes were observed between calibration and WITHfeed paradigm ($p = 0.209$). In addition, the comparison between the online paradigms showed no significant difference ($p = 0.337$). This

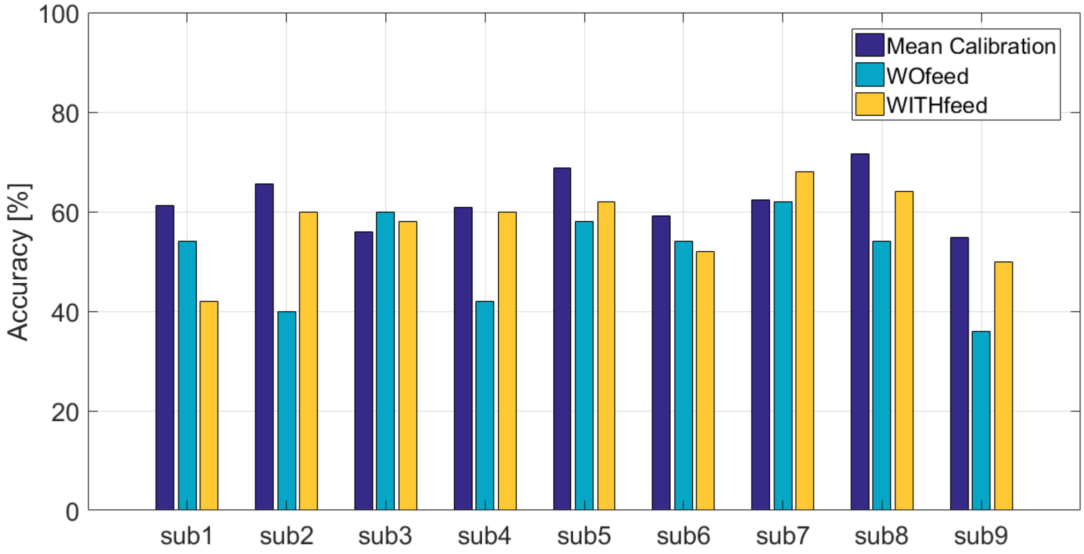

Figure 6.3: Comparison of the accuracy among all paradigms. The dark blue bar represents the mean accuracy among the five optimal classifiers, selected for majority voting during calibration. The bars in light blue and yellow depicts the WOfeed and WITHfeed accuracies, respectively.

implies that for analysing the results of the WITHfeed session, the classification accuracy of the calibration can be used as a reference.

When evaluating the effect of feedback, the TPR comparison between WOfeed and WITHfeed showed no clear pattern (see Figure 6.4). This difference between WITHfeed-WOfeed, revealed no effect in three subjects, increase in four, and just two with decreasing TPR as hypothesised. The non significant difference of the TPR was confirmed by the repeated measures ANOVA ($p = 0.708$). On the other hand, TNR increased for 6/9 subjects during the WITHfeed session. However, the repeated measures ANOVA for the TNR, determined that this change in control trials detection between WOfeed and WITHfeed paradigms was not significant ($F(1, 8) = 1.593, p = 0.242$).

The combination of TNR and ACC results, show that the implemented visual feedback does have an effect on subjects' attention. It increases their concentration on dorsiflexion (higher TNR) and improves their understanding of the experiment (higher accuracy with respect to the WOfeed session).

Combining all online performance metrics, results show that for most subjects, feedback did not increase their concentration during auditory oddballs, as no significant decrease in the TPR was observed. On the contrary, feedback was more likely to increase TPR, TNR or both, suggesting higher separability between attention and control trials, which was translated into significantly higher accuracy with respect to WOfeed.

	TPR (WO)	**TPR (WITH)**	**TNR (WO)**	**TNR (WITH)**
sub 1	28.00%	28.00%	80.00%	56.00%
sub 2	36.00%	60.00%	44.00%	60.00%
sub 3	64.00%	52.00%	56.00%	64.00%
sub 4	56.00%	72.00%	28.00%	48.00%
sub 5	88.00%	40.00%	28.00%	84.00%
sub 6	24.00%	24.00%	84.00%	80.00%
sub 7	52.00%	52.00%	72.00%	84.00%
sub 8	44.00%	56.00%	64.00%	72.00%
sub 9	52.00%	88.00%	20.00%	12.00%

Table 6.8: Performance of the online testing paradigm for each subject and group (WOfeed/WITHfeed)

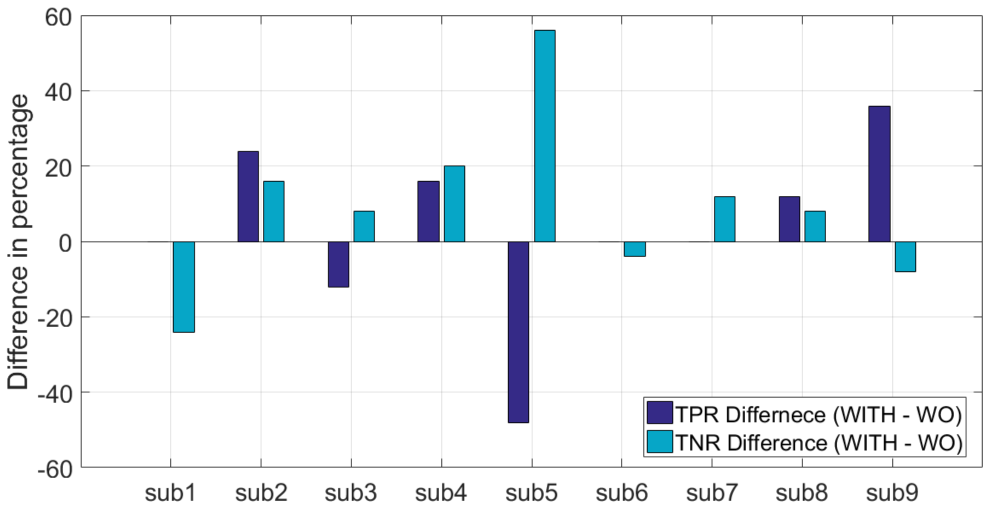

Figure 6.4: Differences in the percentages of TPR (dark blue) and TNR (light blue) between WITHfeed and WOfeed for every subject.

Chapter 7

Discussion

7.1 Discussion

The main objective for this study was to evaluate the effect of feedback in an adaptive BCI configuration with attention variations. Studies [44, 42] have shown that attention alternation has a significant effect on the preparation and execution of the movement, reflected in changes in the temporal features of the MRCP. This has an important implication in designing real-time BCI systems, pointing out the need to adjust these systems to the acute environment. Our hypothesis was that real time feedback would enhance participants' focus, and thus the rehabilitation effect of the BCI system would improve, as the increased level of attention means greater neuroplasticity [46].

7.1.1 Channel Location

The areas most affected by attention diversion in this study, correspond to fronto-central lobe (FC3 and FC4), parieto-central lobe (CP2) and parietal lobe (P2 and Pz). These findings, partially agree with Aliakbaryhosseinabady et al. [47], who found the highest classification accuracy between focused and dual task attention diversion, in the central and fronto-central lobes. The good performance of parietal channels might be reconduced to physiological reasons. In fact, subjects were instructed to be careful to the visual cue and to the feedback. This continuous visual focus may have activated the parietal cortex more than speculated before the experiment. The parietal cortex, as explained in chapter 1.2, is responsible for spatial orientation and sense integration. This would explain its particularly marked activation and its involvement in attention diversion.

7.1.2 Processing

In order to optimise the setup, an optimisation of the feature set was carried out. Results showed significantly higher performance of the spectral features with respect to the temporal ones. In addition, no statistically significant increase in accuracy was observed when extracting both temporal and spectral features. The high variability of this last feature set, suggest that the spectral signal content is indeed the most informative. Similar results were obtained in [47], where time-frequency features (event-related spectral perturbation representing the power of the wavelet coefficients in each window), revealed superior accuracies than MRCP-based temporal features.

However, despite feature optimisation, the obtained mean accuracy during the online testing without feedback ($51.11 \pm 9.39\%$) was considerably lower than in [47], ranging from 60-70% depending on the area and extracted feature set, using Linear Discriminant Analysis. The classifier analysis carried out during the first pilot showed that Decision Trees and SVM retrieved the highest accuracies when detecting control and attention trials. Antelis et al [48], also applied SVM - which using time-frequency features to represent two attention states while performing a motor task - yielded to 76.37% average classification accuracy. A more in depth analysis of the optimal classifiers for detecting different attention states was carried out by Fathy and Eldawlatly [49]. They evaluated Linear Discriminant Analysis, Naive Bayes Classifier and SVM with spectral features of single-channel data, resulting in $67.8 \pm 5.6\%$, $67.2 \pm 4.9\%$, $65.2\acute{s} \pm 3.1\%$ average accuracy, respectively.

However, due to the novelty of the project, few studies have been found for comparison. The main line of investigation found regarding BCI and MRCP is focused on movement prediction [50, 51, 52, 53], rather than their relationship with attention.

During the second pilot study a significant decrease in accuracy was noticed in the online trials compared to calibration. Furthermore, after analysing the data from the second study, not clear patterns could be observed from TPR and TNR variations. This means that the differences between groups were not as evident as we had hypothesised. In addition, within group variations showed rather unique subject responses. For the aforementioned reasons, the study was changed from a parallel study to a crossover study.Subject specificity is of particular interest in this study since it might relate to how neuroplasticity is induced in different patients. This unique response between stimulus and plasticity could suggest that, despite the common pathology, it is important to tailor BCI used in clinical setting with parameters that fit each individual patient.

7.1.3 Feedback analysis

Following this subject-specific processing, the main experiment showed that feedback increases general attention, which is related to the TPR and the TNR. TPR doesn't have a clear behaviour since it had no effect in three subjects while it increased in four other subjects and finally it decreased in two other subjects. This contradicts the prior hypothesis that expected an increase the false negative rate (attention trials classified as control), which would therefore decrease the TPR. On the other hand, TNR increased in six out of nine subjects, meaning that the precision in identifying classes and separating control from attention, increases. Thus when a control trial is shown to the classifier the classification is done correctly. Overall, the feedback increased the attention but it cannot be clearly established whether this has a direct effect on attention to perform the main task. In fact, an increase in TPR and TNR means that the feature spaces are more separated and thus the subjects are more focused during control trials but not during attention trials. This may indicate that subjects are better in shifting attention between tasks.

In clinical settings attention can be diverted easily and thus our aim was to simulate these attention conditions in our BCI system in the laboratory. However, in order to recreate the effect of the clinical environment, the study was limited to divert subjects' attention using dual tasking (dorsiflexion and oddball sequence counting), instead of a complete unfocused state.

7.1.4 Subjects' fatigue during the experiment

Attention was split into two tasks concurrently and even though dorsiflexion was easy to perform the auditory one was complex according also to the subjects. Despite the simplicity of the movement, users complained mental fatigue and sleepiness, throughout the three sessions of fifty dorsiflexion repetitions.

We speculate that sleepiness came from the simplicity of the movement and its repetition across the three sessions. We suppose that mental fatigue was due to the auditory oddball task given aside the main task.

The system's hardware comprehended a LCD screen which was not provided with anti-reflective layer and thus, darkness was needed for the use to see the visual queue appropriately. Artificial light was off in order to avoid unwanted interference with the EEG signal. Lack of light in the room is also believed to be a factor that contributed to sleepiness.

To enhance focus and reduce the aforementioned negative effects, users were provided with coffee, if desired.

Although not measured, for some subjects, fatigue had an effect on the attention paid during the experiment.

7.1.5 Future work and improvements

In regards to subject fatigue, lowering the number of repetitions in each session, from fifty to 30 for instance, might be beneficial in avoiding subject sleepiness and thus, increasing attention during the whole duration of the experiment.

Although the results obtained during this study only suggest a general, rather than task-specific, increase in subjects' attention. Their validation is restricted to the low number of participants. Encouraging healthy subjects to participate was an issue during the development of the project. Therefore, the improvements in the experimental set up mentioned before, to save time and reduce subjects' fatigue, are thought to facilitate participants' recruitment, and thus, improve the validation of the results.

Finally, in accordance to the subject-specific processing, future implementations of online feedback should consider time-frequency features, where both frequency bands and timing are selected based on the greater differences in the attention states.

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