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Do I have a third arm? Towards a Supernumerary Motor Imagery Brain-Computer Interface in Virtual Reality

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“Ni usted ni yo necesitamos presentación:
tenemos tres cosas en común: esta tierra, la vida y la muerte.
En eso somos semejantes, casi amigos.
Al menos, hay que vivir con esa ilusión de amistad
que es básica para la soliradidad humana.”
— GONZALO ARANGO

“...Yo digo que no hay quien crezca
más allá de lo que vale
—y el tonto que no lo sabe
es el que en zancos se arresta.
Y digo que el que se presta
para peón del veneno
es doble tonto y no quiero
ser bailarín de su fiesta...”
— SILVIO RODRIGUEZ

“...Levanta tu espada de la dignidad y sapiencia
carga tus derechos, dispara tu fusil de conciencia
ya que es la ignorancia la que hace a los pueblos pobres
y los hombres de rodillas son mas rodillas que hombres...”
— CANSERBERO

“If I have seen farther than others,
it is because I stood on the shoulders of giants.”
— SIR ISAAC NEWTON

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I would like to do the official acknowledgments in the document language (English). However, the personal ones are going to be in Spanish, my mother language, because it is more natural to me to say thanks to those people that participated inside of this journey named "master degree".

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ABSTRACT

Brain-Computer Interface (BCI) opened the possibility of communicating the human with systems and devices using brain signals. This area has inspired researchers to develop several applications such as medical rehabilitation of disabled people, robotic prostheses, games, and assisted virtual reality (VR) scenarios. In effect, VR is currently employed to improve the BCI's reliability through realistic and natural training and feedback. Motor imagery Brain-Computer Interface (MI-BCI) is a paradigm widely used for controlling external devices by imagining bodily movements. So far, nevertheless, MI-BCI has only used embodied limbs for the imaginary tasks, even though that psychology has conclusively demonstrated the existence of body transfer illusions (rubber hand illusion).Thus, this thesis studies and explores the inclusion of an imaginary third arm as a part of the control commands for MI-BCI while comparing the effectiveness of using the conventional arrows and fixation cross as training step (*Graz* condition) against a first-person view of a human-like avatar performing the corresponding task (*Hands* condition). Both conditions made in a VR scenario. Ten healthy subjects participated in a two-session experiment involving open-close hand tasks (including a third arm that comes out from the chest). The EEG analysis shows a strong power decrease in the sensory-motor areas for the third arm task in both conditions. Furthermore, the offline classification results show that a third arm can be effectively used as a control command (accuracy $> 0.62\%$). Likewise, Hands condition (67%) outperforms Graz condition (63%) significantly, suggesting that the realistic scenario can reduce the abstractness of the third arm and improve the performance, however, this condition induces a cognitive load. Finally, with this thesis, a door is open towards the creation of a supernumerary MI-BCI system with the inclusion of non-embodied motor imagery tasks.

Keywords: Brain-Computer Interface. Virtual Reality. Rubber Hand Illusion. Cognitive Load. Electroencephalography.

Eu tenho um terceiro braço? Em direção a interfaces supranumerárias cérebro-computador de imaginação motora em realidade virtual.

RESUMO

As interfaces cérebro-computador (BCI) abriu a possibilidade de comunicar ao hómem com sistemas e dispositivos usando sinais cerebrais. Essa area tem inspirado pesquisadores a desenvolver várias applicações, como reabilitação médica de pessoas com deficiência, próteses robóticas, jogos e cenarios assitivos em Realidade Virtual (VR). De fato, VR está atualmente sendo empregada para melhorar a confiabilidade do BCI por meio de treinamentos e feedback realisticos e naturais. Imaginação motora Interface cérebro-computador (MI-BCI) é um paradigma amplamente utilizado para controlar dispositivos externos, imaginando movimentos corporais. Até agora, no entanto, o MI-BCI usou apenas membros incorporados para as tarefas imaginárias, mesmo que a psicologia tenha demonstrado conclusivamente a existência de ilusões de transferência do corpo (ilusão mão de borracha). Assim, esta tese estuda e explora a inclusão de um terceiro braço imaginário como parte dos comandos de controle do MI-BCI, comparando a eficácia do uso das setas convencionais e da cruz de fixação como etapa de treinamento (condição *Graz*) contra uma visão em primeira pessoa de um avatar semelhante ao humano executando a tarefa correspondente (condição *Hands*). Ambas condições feitas num cenário de VR. Dez indivíduos saudáveis participaram de um experimento de duas sessões envolvendo tarefas de mão aberta. A análise do EEG mostra uma forte queda de potência nas áreas sensório-motoras para a tarefa do terceiro braço em ambas as condições. Além disso, os resultados da classificação off-line mostram que um terceiro braço pode ser efetivamente usado como um comando de controle (accuracia $> 0.62\%$) Da mesma forma, a condição Hands (67%) supera significativamente a condição Graz (63%), sugerindo que o cenário realista pode reduzir a abstração do terceiro braço e melhorar o perfomance, no entanto, esta condição induz uma carga cognitiva. Finalmente, com esta tese, abre-se uma porta para a criação de um sistema MI-BCI supranumerário com a inclusão de tarefas de imaginação motora não incorporadas.

Palavras-chave: Interface Cérebro-Máquina, Realidade Virtual, Ilusão Mão de Borracha, Carga Cognitiva, Eletroencefalografia.

LIST OF ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
BCI	Brain-Computer Interface
BNCI	Brain-Neural Computer Interaction
BP	Band power
C	Classifier
CAR	Common Average Referenced
CSP	Common Spatial Filter
EC	European Commission
ECoG	Electrocorticography
EDA	Electrodermal Activity
EEG	Electroencephalography
EKG	Electrocardiogram
EMG	Electromiography
ER	Error Rates
ERD	Event-Related Desynchronization
ERS	Event-Related Synchronization
ers	event-related spectrum
ERSP	Event-Related Spectral Perturbation
FBCSP	Filter Bank Common Spatial Pattern
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
fMRI	Funcional Magnetic Resonance Imaging
G	Graz
GSR	Galvanic Skin Response
H	Hands
HCI	Human-Computer Interaction
HMD	Head-Mounted Display
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
KNN	K-Nearest Neighbor

LDA	Linear Discriminant Analysis
LH	Left Hand
LR	Logistic Regression
LSL	Lab Streaming Layer
MEG	Magnetoencephalography
MI	Motor Imagery
MI-BCI	Motor Imagery Brain-Computer Interface
MIQ	Movement Imagery Questionnaire
mRMR	maximum Relevance Minimum Redundancy
mV	millivolts
NF	Number of Features
NTP	Network Time Protocol
PCA	Principal Component Analysis
PSD	Power Spectral Density
RH	Right Hand
RHI	Rubber Hand Illusion
RS	Resting State
RT	Reaction Times
SNR	Signal-to-noise-ratio
SSVEP	Steady-State Visual Evoked Potential
SVM	Support Vector MAchine
SW	Size of the time Window
TH	Third Hand
UFRGS	Federal University of Rio Grande do Sul
VEP	Visual Evoked Potential
VMIQ	Vividness of Movement Imagery Questionnaire
VR	Virtual Reality
WD	Wavelet Descomposition
WM	Working Memory
WMC	Working Memory Capacity

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1 INTRODUCTION

1.1 Scope

This master thesis focuses on Brain-Computer Interface (BCI), mainly, towards the development of a Motor Imagery (MI) BCI system that includes an imaginary third arm as a control command. In order to explore the influence of the third arm approach in the BCI system, this work uses two training conditions in Virtual Reality (VR): the traditional Graz paradigm and a realistic human-like avatar. For both conditions, this thesis comprises an exploration of the feature extraction and classification methods, cognitive load measures, and a spectral EEG analysis.

1.2 Motivation

Brain-Computer Interface is the technology that translates the brain signal into an output command for controlling machines (a complete definition can be found in the next chapter). It has recently been a hot topic in research due to two aspects: *a*) Rehabilitation and interaction, opening countless opportunities for impaired people and alternative user interfaces; and *b*) BCI pipeline, which includes several research areas such as Signal Processing, Pattern Recognition, Machine Learning, Human Factors, Psychology, among others.

Indeed, the importance of this emergent area can be visualized by the creation and execution of the research project “BNCI Horizon 2020: The Future of Brain-Neural Computer Interaction” by the European Commission (EC). This project comprises 12 European partners with a solid background in BCI. Its primary goal is to make a road-map and sketch up the future of BCI for the next ten years or more [Graz 2015].

Meanwhile, in Brazil, efforts in such directions have been made through the National Institute for Brain-Machine Interfaces (INCEMAQ) supported by the National Institutes Program of Science and Technology of the National Council for Scientific and Technological Development CNPq/MCT [AASDAP 2016]. Its main aim is to establish and increase the scientific research in BCI, involving around 16 Universities from 9 states of the country. Unfortunately, the research on BCI in the Rio Grande do Sul state is still beginning, and there is not an established research group working in this area [CNPq 2016]. For this reason, it is essential that the Federal University of Rio Grande do Sul (UFRGS), and its Institute of Informatics begins formally with BCI research. Therefore, this work is addressed to contribute inside BCI research, exploring the importance of a supernumerary BCI system, which could be used as a control interface for an exoskeleton or a customized avatar in a VR application.

1.3 Problem Statement

Despite BCI being a promissory and useful technology, there are still several challenges to be faced. Chavarriaga et al. [Chavarriaga et al. 2017] discuss concrete research avenues and guidelines to overcome common pitfalls in BCI. That work is the outcome of a meeting held at the workshop "What’s wrong with us? Roadblocks and pitfalls in designing BCI applications." They summarize four main topics that influence any closed-loop BCI system: a)End Users; b)Feedback and user training; c)Signal processing and decoding; d)Performance metrics and reporting. Meanwhile, in this document three categories are highlighted which represent challenges inside BCI:

- **Hardware challenges:** The reliability of the recording devices assures the successfulness of the BCI application. Such devices should have high transfer rates and signal-to-noise-ratio (SNR) so that the recorded signal can be accurate and relevant to the phenomena to be studied. Likewise, the measurement system should be as less invasive and portable as possible in order to guarantee the safety and comfort of the user. Unfortunately, the development of equipment that reach these requirements is often expensive [Abdulkader, Atia and Mostafa 2015].

- **Software challenges:** The software development for BCI application is the core of the research activities. Because it includes different stages such as signal processing, extracting and classification of features. Here, the challenge is to keep the enough relevant information to identify and subsequently classify the mental state of the user, taking into account that the noise could come from both the electronic device (line noise) or artifacts (brain activity unrelated to the stimulus). Moreover, the software should have short time processing and high accuracy rates in the classification in order to give a right and fast feedback to the user [Lotte 2014].

- **Application challenges:** The design of the application or interface that the user will use should follow several criteria based on human factors and usability. Indeed, Lotte et al. [Lotte et al. 2018] recently highlighted the importance of thinking on the psychological factors (cognitive load, user modeling, etc.) of the user during the application. In effect, the training task should include critical feedback so that the user can easily understand the action to be executed and improving thus its performance. However, it is currently hard to choose the right feedback presentation, and it should be a motivating and engaging environment, besides natural and realistic.

This thesis addresses the application and software challenges. In the first one, the thesis proposes the inclusion of a imaginary third arm, as a control command, in a Motor Imagery Brain-Computer Interface (MI-BCI) system. Such approach is evaluated using two training conditions in VR: traditional arrows and cross fixation (Graz), and a human-like avatar. Furthermore, this thesis uses a framework to explore and evaluate the feature extraction and classification steps of the proposed application in both training conditions.

1.4 Objectives and Approach

The main objective of this thesis is to investigate the possibility of including an imaginary third arm inside an MI-BCI system. In order to reach this aim, the next specific tasks are proposed:

1. Review the state-of-art of methods, approaches and theoretical terms inside BCI.

2. Create two training scenarios in Virtual Reality.
3. Record EEG data in a BCI paradigm.
4. Create a methodological framework to study and explore the window time and frequency bands in three different classifiers.
5. Analyse the EEG patterns associated with Motor Imagery activity.
6. Evaluate the performance of the classifiers for separating the imaginary third arm from the other imaginary task and resting.
7. Compare the EEG activity and classification performance in the two training conditions.
8. Study the user's cognitive load caused by the proposed training conditions.

1.5 Contributions

In addition to the dataset and codes that go to be available online, the scientific contributions of this thesis can be sumarized as follow:

1. EEG patterns of motor imagery activity (ERD/ERS) were found when the users performed an imagery task of a hand movement of a third arm emerging from the chest.
2. Such imaginary third hand was successfully classified from other imaginary tasks (left and right hand), and resting state, advancing the findings reported by Bashford and Mehring [Bashford and Mehring 2016].
3. The results (see Table 2.1) suggest that the classification distinguishes the third arm from the left hand and the resting state conditions with higher accuracy rates than it does from the right hand. This seems to be related to handedness.
4. The thesis goes further than the previous findings done by Skola and Liarnokapis [Skola and Liarokapis 2018] because all comparisons were made in VR, eliminating the bias that there exist when the realistic human-like VR scene is compared against the Graz parading made in a monitor-based presentation.

1.6 Thesis Outline

This document has the follow structure for the remaining chapters:

- Chapter 2 summarizes the basic concepts concerning to Electroencephalography (EEG) and Brain-Computer Interface (BCI), as well as Virtual Reality (VR) technology, cognitive load and body transfer illusion.
- Chapter 3 deals with discussion of the related works regarding Motor Imagery Brain-Computer Interface, BCI applications that use VR scenarios and how BCI have been used to study the third arm illusion.

- Chapter 4 describes the materials and procedures used for recording the EEG as well as the methods employed for the offline analysis.
- Chapter 5 presents the results obtained from the offline analysis of the EEG data.
- Chapter 6 also presents the results of the exploratory study of the features and classifiers used for the BCI loop.
- Chapter 7 describes the cognitive load studies and the questionnaire answers.
- Chapter 8 sums up the final remarks, limitations, contributions and future works that can be done.

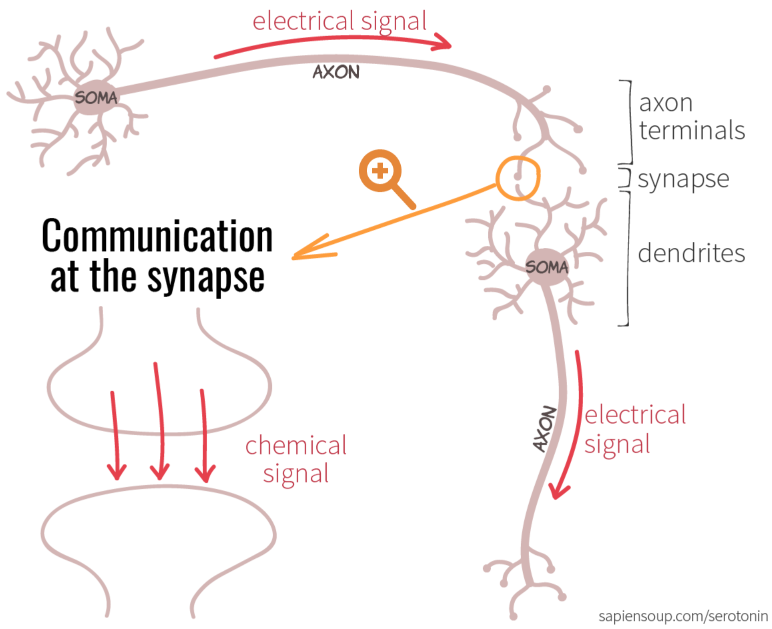
2 BACKGROUND

This chapter introduces the concepts, methods, and terminology necessary to understand the rest of the document and the thesis's contributions.

2.1 Electroencephalography

The human brain is an outstanding system. Our understanding of how it works has inspired scientists and engineers to create machines [Fiorini 2017]. In effect, neurons -the fundamental units in the brain- use both chemical and electrical signals for transmitting information [Morrison 2018]; a typical neuron has three fundamental parts: soma (or cell body), axon and dendrites. In the soma, the nucleus and most of the neuron's organelles are placed. The axon is a "wire" that transports the electrical signals (known as action potentials) to other cells; its extension could reach long distances, i.e., from the spinal cord to the muscle cells in the feet. Finally, the dendrites are a densely ramified extension of the soma; they are responsible for receiving signals from other neurons. The connection between neurons for transmitting information is called a synapse [Reece 2016]. The figure 2.1 shows a simplified version of a neuron with the mentioned parts.

Figure 2.1 – A simplified version of the neuron with its fundamental parts



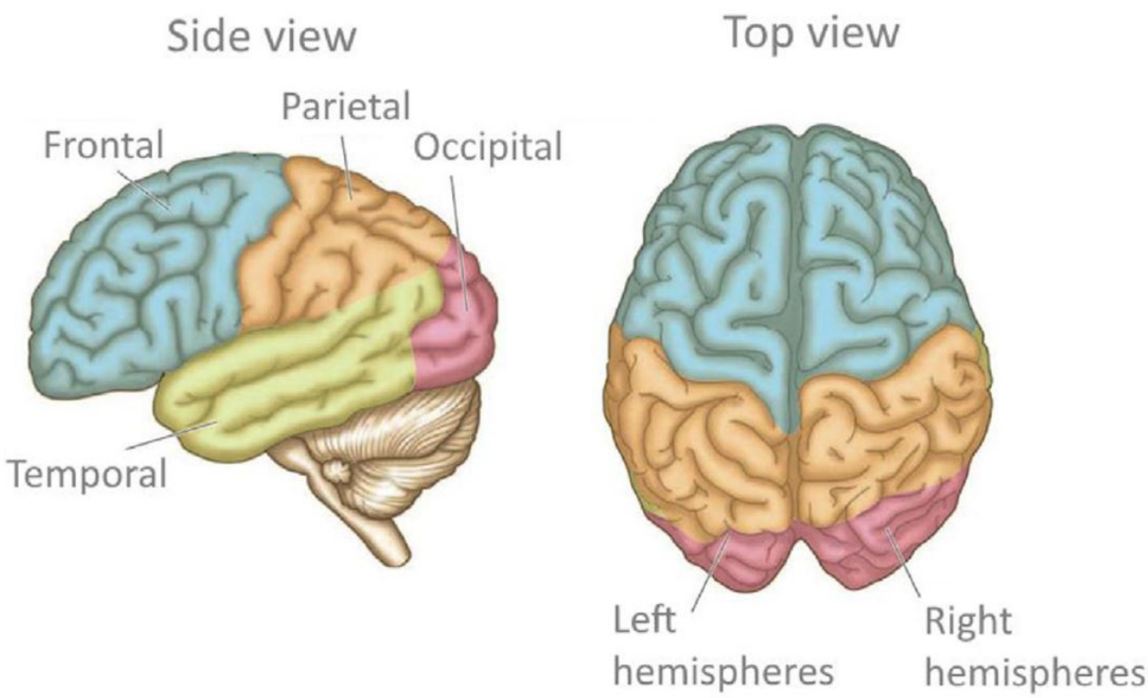
Source: https://goo.gl/t298dC

The electrical activity of a resting neuron is around -70 millivolts (mV), depending on the interaction with other neurons, it could be more or less negative [Morrison 2018]. The contributors of these measurable signals could be [Cognition and Unit 2009]: 1) Action potentials traveling along the axons; 2) currents through the synaptic connections, and 3) dendrite's currents from synapses to the soma. The currents produced by a vast number of neurons reach the scalp surface creating voltage differences that can be measured using electrodes placed on the skin surface of the head. This technique is known as Electroencephalography (EEG) [Bronzino 1970]. Hans Berger, a German psychiatrist, made the first attempts for recording EEG in humans in 1924 [EK and LC 2016].

2.1.1 10-20 international system

The brain has been divided into several regions to facilitate its study and discovering main functions associated with the corresponding brain area. Furthermore, the brain is separated by two hemispheres (left and right) [Morrison 2018]. The figure 2.2 shows the main brain divisions (Frontal, Temporal, Parietal and Occipital lobe); and the two hemispheres (Left and Right).

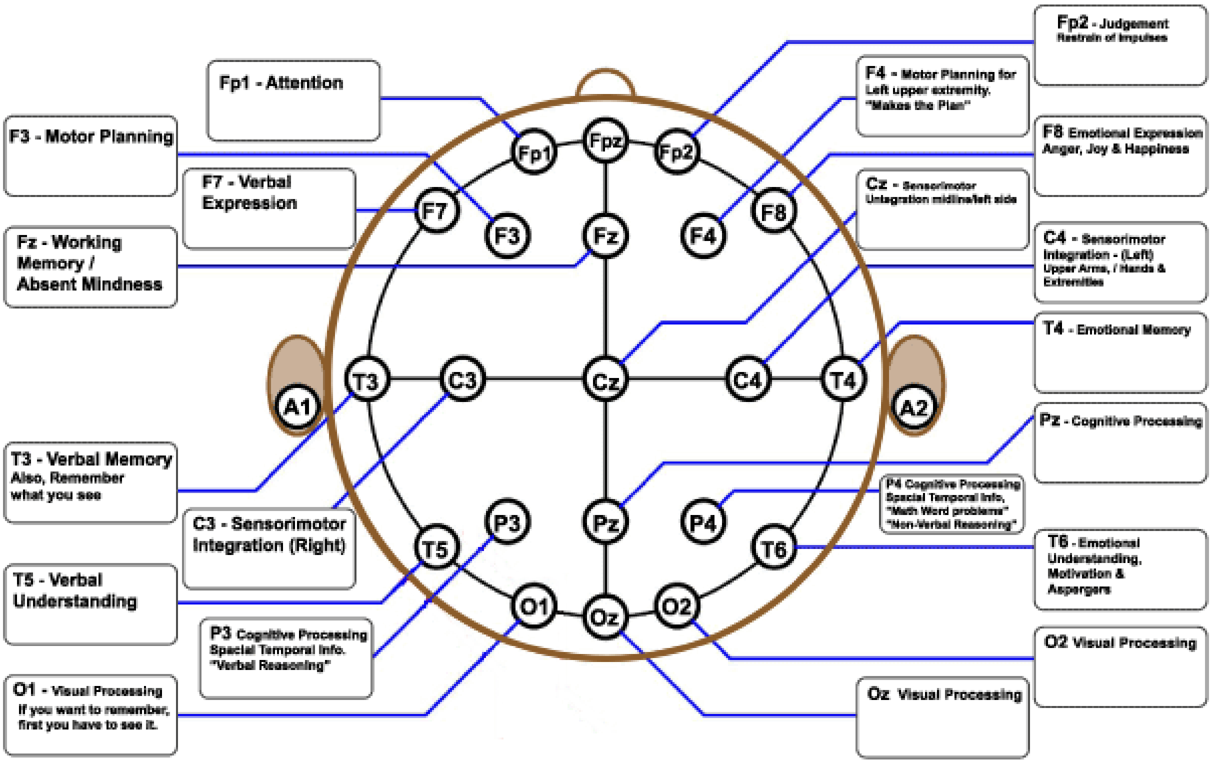
Figure 2.2 – Brain regions from two views.



Source: [Lim et al. 2018]

Such division is an essential key for consolidating a standardized system for EEG electrode placement. In effect, the International Federation of Societies for Electroencephalography and Clinical Neurophysiology created the 10-20 system [The Ten Twenty Electrode System: International Federation of Societies for Electroencephalography and Clinical Neurophysiology 1961]. It consists of an array of electrodes whose positions follow specific anatomical landmarks on the head. Each electrode is separated by 10% and 20% distances. The figure 2.3 shows the 10-20 system and in each electrode of this array, the primary function associated with the brain area. An interesting aspect regarding this system is its nomenclature, the letter comes mainly from the brain lobes (excepting the central part), and the number from the hemisphere (odd numbers for left and even for right), e.g., an electrode located at the temporal lobe and left hemisphere is named as T3; whereas, one at frontal lobe and right hemisphere is as F4. The electrodes on the central axis of the head take the letter "z" as the number.

Figure 2.3 – 10-20 electrode position with some of its main brain function for each electrode.



Source: adapted from https://goo.gl/iA59Qx

2.1.2 Brain neural oscillations

The EEG signals are characterized by its neural oscillations rhythms that can be dived into five bands or spectrums that are used to study some cognitive states [Abo-Zahhad Sabah Mohammed Ahmed 2015, Herrmann et al. 2016]:

- **Gamma [γ]**: These fast waves (more than 30Hz up to 200Hz) are usually studied during conscious perception. Typically, studying these signals is hard due to the high amount of artifacts caused by the muscle movements and its low voltage amplitude ($< 2\mu V$). Gamma oscillations are related to attention information processing, working and long-term memory. Also, gamma rhythms have played an important role in psychiatric disorders such as epilepsy, schizophrenia and Alzheimer's disease [Amo et al. 2017, Herrmann and Demiralp 2005].

- **Beta [β]**: beta oscillations range between 12 and 30 Hz, although it is common to divide the band into low beta (12 to 20Hz) and high beta (20 to 30hz). The modulation of this electrical activity has mainly been associated with motor and cognitive processes, decision making and sensorimotor interaction. These rhythms are primordially found at frontal and central regions. Beta waves have an amplitude of $< 2\mu V$ [Kropotov 2016, Neuper and Pfurtscheller 2001].

- **Alpha [α]**: alpha oscillations can be observed during sensory stimulation, in a frequency range from 8 to 12Hz. Alpha rhythms play a fundamental role for cognitive processing, attention, inhibition (self-regulation), and psychological factors such as cognitive load and task engagement, as well as an indicator of general intelligence (g factor). The alpha rhythms are frequently found at parietal and frontal lobes with an amplitude of 10 and $20\mu V$ [Bazanova and Vernon 2014, Malik and Amin 2017].

- **Theta [θ]**: theta waves are associated with daydreaming, memory processes, and sleep. Since the Hippo-campus (a region responsible for memory functions) exhibits theta oscillations for communicating with the frontal cortex, theta rhythms are involved in memory encoding and retrieval. Interesting, if the user is not performing any attention or cognitive activity, the exhibition of theta oscillations can be related to brain disorders, depression, and stress. Whereas, theta waves present benefits in creativity, relaxation and intuition [Herrmann et al. 2016, Abhang, Gawali and Mehrotra 2016]. Theta signals are found in a frequency range of 4-8 Hz with an amplitude of $< 100\mu V$.

- **Delta [δ]**: delta oscillations characterize to be a high-amplitude (75 to $200\mu V$) waves with less than 4Hz. These brain signals are associated with deep sleep stages and cortical plasticity. Also, delta rhythms play an important role in event-related studies because the P300 (peak amplitude after 300ms the stimuli onset) are mainly composed of delta and theta oscillations [Harmony 2013, Guntekin and Basar 2016].

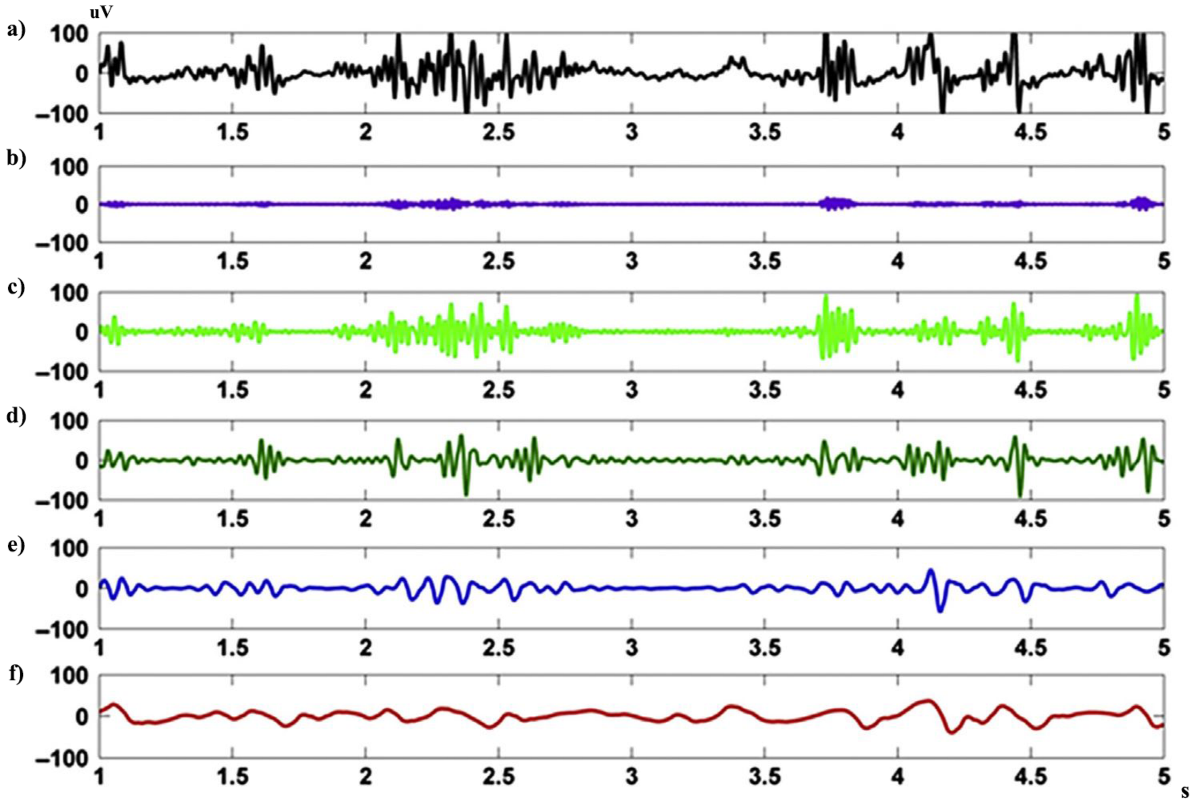
Figure 2.4 shows the frequency bands described above. This thesis mainly works with beta and alpha oscillations.

2.1.3 EEG applications

Since that EEG is a "window" regarding the mental state of the user (either human or animal) and the ongoing processes of the brain during the performing of an activity, it has been widely used in several applications such as:

- Clinical applications: the EEG data is used in medical applications, namely, the diagnosis of neurophysiological disorders such as epilepsy, dementia, autism; head injuries such as brain tumor and strokes; finally, sleep disorders and anesthesia monitoring in surgical interventions (for an extensive review see [Siuly, Li and Zhang 2016]).

Figure 2.4 – Frequency bands. a) raw signal; b) Gamma (30-100+ Hz); c) Beta (12-30 Hz); d) Alpha (8-12 Hz); e) Theta (4-7 Hz); f) Delta (0-4 Hz).



Source: https://goo.gl/TfMQ9o

- Psychology and neuroscience: It is evident the link between neuroscience and psychology with EEG. This technique has been widely used for understanding brain functions such as memory, emotion, perception, vision, motor imagery, language among others. Experimental approaches such as EEG have been fundamental for brain research due to the possibility of monitoring real-time brain activity in front of different situations [Dickter 2014].

- Brain-Computer Interface: EEG, in comparison of other recording techniques, is non-invasive, portable and relatively cheap. These features enable the use of electrical brain activity for communicating and controlling external systems (computers, robotic prosthesis, games). This application is known as Brain-Computer Interface (BCI). The next part of this thesis focuses on BCI.

2.2 Brain-Computer Interface

Throughout the last decades, human beings have sought different alternatives to communicate with machines or systems. In this context, Brain-Computer Interface (BCI) plays an important role, motivated by overcoming the difficulties experienced by impaired people [Neuper and Pfurtscheller 2010] or, just by developing a non-mechanical user interaction for robotic prostheses, games and assisted virtual reality (VR) scenarios [Gert et al. 2011] [Brunner et al. 2011]. BCI is the technology that enables a bodiless communication with machines or devices;

this is done using the translation of brain signals elicited during a specific task into command outputs.

Depending on the nature of such task, BCI is divided into passive, active and reactive [Zander and Kothe 2011]: passive systems use signals that arise without voluntary control; it is used fundamentally to asses mental states and enhancing the human-computer interaction [Zander et al. 2010]; active BCI works with the self-induced brain activity produced by the user, independently of external events; such activity is used as a control signal [Zander et al. 2010]; and, finally, reactive task relies on the signals elicited by the reaction to external stimuli, these signals could be used for controlling an application too [Donchin, Spencer and Wijesinghe 2000]. Furthermore, BCI has two modes of operation: synchronous, where a cue is shown to the user for enhancing the elicit of brain signals to control the device; asynchronous, no cue stimulus is presented and the user has to generate the mental state for himself to control the device. This thesis studies an active and synchronous BCI system.

A typical structure of a BCI system consist of five main stages: signal acquisition, signal processing, feature extraction, classification, and feedback application.

2.2.1 Signal acquisition

BCI relies on the brain signals recorded from the user to decode the mental states into output commands. Thus, several techniques have been used in order to collect this data; they differ mainly in aspects such as kind of variable (electrical, magnetic, metabolic), temporal and spatial resolution, the level of invasiveness and its portability. Table 2.1 shows the most representative recording methods inside the BCI literature [Nicolas-Alonso and Gomez-Gil 2012]:

Table 2.1 – The most representative data recording techniques for BCI.

Recording method	Activity measured	Temporal resolution	Spatial resolution	Risk	Portability
Electroencephalography (EEG)	Electrical	∼0.05s	∼10mm	Non-invasive	Portable
Electrocorticography (ECoG)	Electrical	∼0.003s	∼1mm	Invasive	Portable
Magnetoencephalography (MEG)	Magnetic	∼0.05s	∼5mm	Non-invasive	Non-portable
Functional Magnetic Resonance Imaging (fMRI)	Metabolic	∼1s	∼1mm	Non-invasive	Non-portable

Source: adapated from [Nicolas-Alonso and Gomez-Gil 2012]

This thesis works with EEG as a recording method; therefore, the next sections focus on this technique.

2.2.2 Signal processing

Usually, the EEG data has artifacts from the eye or muscle movement, heartbeat or line noise (frequency 60hz). In order to enhance the signal-to-noise ratio (proportion of useful signal over noisy signal) of the brain signal, several digital processing techniques are employed, namely, digital filters such as Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters, or sub-sampling frequency methods as well as re-reference signals (spatial methods) or normalization [Bashashati et al. 2007]. Likewise, statistical approaches can be used for cleaning the data such as Independent Component Analysis (ICA) or Principal Component

Analysis (PCA). Although these methods are also used as feature extraction and dimensional reduction technique.

2.2.3 Feature extraction

This step aims to transform the filtered EEG data into a structure of small elements (features) that retain the meaningful information of the brain activity, i.e., removing the irrelevant data meanwhile the most representative is retained. This step is fundamental for BCI because EEG signals are high-dimensional data so reducing the original dimension into a feature space can enhance the classification [Nicolas-Alonso and Gomez-Gil 2012]. There are three main sorts of information to be extracted from the EEG data [Lotte 2014]: a) spatial data, which describes the place of the headset where the signal activity occurred; b) spectral data, which describes the power of some specific frequency bands; and c) temporal data, which consist of the variation of signal values over time. The most relevant methods for feature extraction are Common Spatial Patterns (CSP), Fast Fourier Transform (FFT), Band Powers(BP), Power Spectral Density (PSD), Wavelet Decomposition (WD), among others [Ramadan and Vasilakos 2017].

2.2.4 Classification

The feature vector (obtained in the previous step) is the input to the classifier in order to assign a class to a set of features that allows identifying the mental state of the user. Initially, a set of labeled observation is used to create a classification model. Subsequently, the model is used to classify new data. The most common classification algorithms are linear classifiers, neural networks, Bayesian classifiers, and nearest neighbor classifier [Lotte et al. 2007]. One indicator of the BCI's successfulness relies on the accuracy of the classifiers used, so the choice of the classification technique should be based on the feature type and number of mental states (classes).

2.2.5 Feedback application

In a closed-loop BCI system (known as online BCI), the feedback application is responsible for giving the user a notion of how well he or she is performing the mental task. Such applications could be a speller program, a robotic prosthesis, a game or merely a loading bar showing the user's performance. The application uses the outcome from the classifier to perform the specific task or event associated with the user's mental state. Meanwhile, in an offline BCI, the users do not directly control anything, the brain activity is recorded for subsequent analysis, but they are receiving a stimulus that helps to elicit the brain activities in order to increase the classification performance [Nicolas-Alonso and Gomez-Gil 2012]. Furthermore, the feedback/stimulus continuously sends markers to BCI's data recordings in order to label specific points in the experiment, mainly when a stimulus is presented [Siuly, Li and Zhang 2016].

The choice of the feature extraction method depends strictly on the neuromechanism used by the BCI. The next section describes the typical neurophysiological patterns used for creating BCI.

2.2.6 Neurophysiological patterns for BCI

The brain can produce different neurophysiological patterns as the result of cognitive responses. These patterns are characterized by their latency (time-locked), voltage amplitude (phase-locked) and spatiotemporal distribution to internal or external stimuli and cognitive responses of the brain. The choice of the neurophysiological phenomena depends entirely on the task to be performed by the BCI system. Indeed, it is a crucial decision because the BCI pipeline would be designed in function of that. BCI systems are classified as either exogenous or endogenous in function of the control signal (neurophysiological patterns) to be used. Such distinction is explained [Siuly, Li and Zhang 2016, Wikidot 2008]:

2.2.6.1 Exogenous BCI

Exogenous BCI is based on the neuron activity elicited by an external stimulus, which could be either visual or auditory [Ramadan and Vasilakos 2017]. In effect, this represents its main advantage because the users do not require extensive training to elicit the control signals and recording this activity only one EEG channel is enough. Two types of brain activity are the most known in exogenous BCI: visual evoked potentials (VEPs) and P300 evoked potentials.

VEPs are characterized by the signal modulation in the visual cortex elicited by a visual stimulus. The amplitude of the signal increases as much as the stimulus is closer to the central visual field [Wang et al. 2006]. For BCI, steady-state VEPs (SSVEPs) are mainly used because their amplitude and phase over remain nearly constant over long time [Ramadan and Vasilakos 2017]. SSVEPs uses high frequencies ($> 6Hz$) stimulus to elicit brain responses at the same frequency (harmonics and subharmonics), mainly in the occipital-parietal regions. BCI based on SSVEPs uses the subject's eye-gaze to a target for identifying the user's intentions.

In the other hand, P300 evoked potentials are brain responses (positive peaks) elicited around 300 ms after the onset of infrequent stimulus. Despite that the P300 does not necessarily require user training, the user could get used to the oddball stimuli, and it has been demonstrated that the less frequent the stimulus the much larger the amplitude of the peaks [Polich, Ellerson and Cohen 1996]. The typical application of SSVEPs and P300 in BCI are the speller systems, where a display shows a matrix of letters, numbers or symbols that represent commands, and the users fixate to the desired target so that the BCI system, after a signal processing, can decode their intention [Zhao, Li and Li 2015, Mugler et al. 2010].

2.2.6.2 Endogenous BCI

Contrary to exogenous BCI, endogenous BCI uses self-regulation brain rhythms without following any external stimuli. One of the control signal most used in this type of BCI system is the sensorimotor rhythms. These oscillations are characterized by temporal, spectral and spatial changes in the Mu (7-12 Hz) and Beta bands (13-30 Hz) at the sensorimotor cortex (see the middle of figure 2.5) [Leeb et al. 2006]. The cortical rhythms are identified by two type of activity:

the attenuation (event-related desynchronization, ERD) or the enhancement (event-related synchronization, ERS) of the power on these bands [Graimann and Pfurtscheller 2006] in relation to the baseline activity. Such modulation could be generated by sensory stimulation, processing cognitive information regarding the production of motor behavior, and mental imagery of motor actions (motor imagery) [Pfurtscheller and Neuper 2001] .

Motor imagery (MI) consists of the mental rehearsal of a motor action without actually perform any movement. This mental simulation actives the same cortical areas that the real movements do [Jeannerod 1995]. Figure 2.5 describes the time–frequency representation of ERS/ERD patterns at right hemisphere and left hemisphere for right hand and foot motor imagery (top and bottom respectively) over time. The hands movement presents a strong ERD activity at C3 while ERS is prominent at Cz, both in mu and beta bands. In the other side, the foot movement shows a weaker ERS activity at C3, whereas at Cz and C4 there is a synchronization at lower beta and alpha (around 10 Hz) bands simultaneously with a desynchronization in mu band. Motor imagery is an essential concept inside BCI because the users, with training, can voluntary elicit the sensorimotor patterns to be used as a control signal in a BCI system [Pfurtscheller and Neuper 2001].

Despite MI being a fundamental constructor of any healthy person, i.e., that all humans could have the capacity of imagining and planning motor activities, some people could face limitations to perform imaginary activities. In such vein, several questionnaires were made in order to subjectively assess the individual ability for imagining motor tasks such as the Vividness of Movement Imagery Questionnaire (VMIQ) [Roberts et al. 2008] or Movement Imagery Questionnaire (MIQ) [Atienza, Balaguer and Garcia-Merita 1994]. The MIQ-3, a recent version of the MIQ, and in different of the VMIQ, assesses three kinds of imagery: internal visual imagery, external visual imagery, and kinesthetic imagery [Williams et al. 2012]. This survey is a 12-item questionnaire to asses the capacity to image four simple movements: a knee lift, jump, arm movement, and waist bend. The MIQ-3 demonstrated excellent psychometric properties, internal reliability, and predictive validity. Therefore, this thesis uses an adaptation of the MIQ-3 questionnaire to the Portuguese language [Mendes et al. 2016] before the experiment in order to asses the user's ability to perform the imaginary task (see Appendix A).

Finally, the ERD/ERS maps presented in the Figure 2.5 can be produced in different ways, mainly using the Band Power (BP) method, Hilbert transformation, Inter-trial variance method, and Event-related spectral perturbation (ERSP) [Pfurtscheller and Silva 1999]. This thesis uses the last method to study the ERD/ERS signals. The ERSP [Makeig 1993, Grandchamp and Delorme 2011] is a generalization of the ERD/ERS activity, which measures the dynamic power changes of the EEG frequency bands relatives to a stimuli onset. Its computation consist in calculate the average power spectrum across the trials for sliding time windows around at time *t* (namely event-related spectrum, *ers*). So the *ers* for a specific frequency *f* and time point *t* is defined as follows:

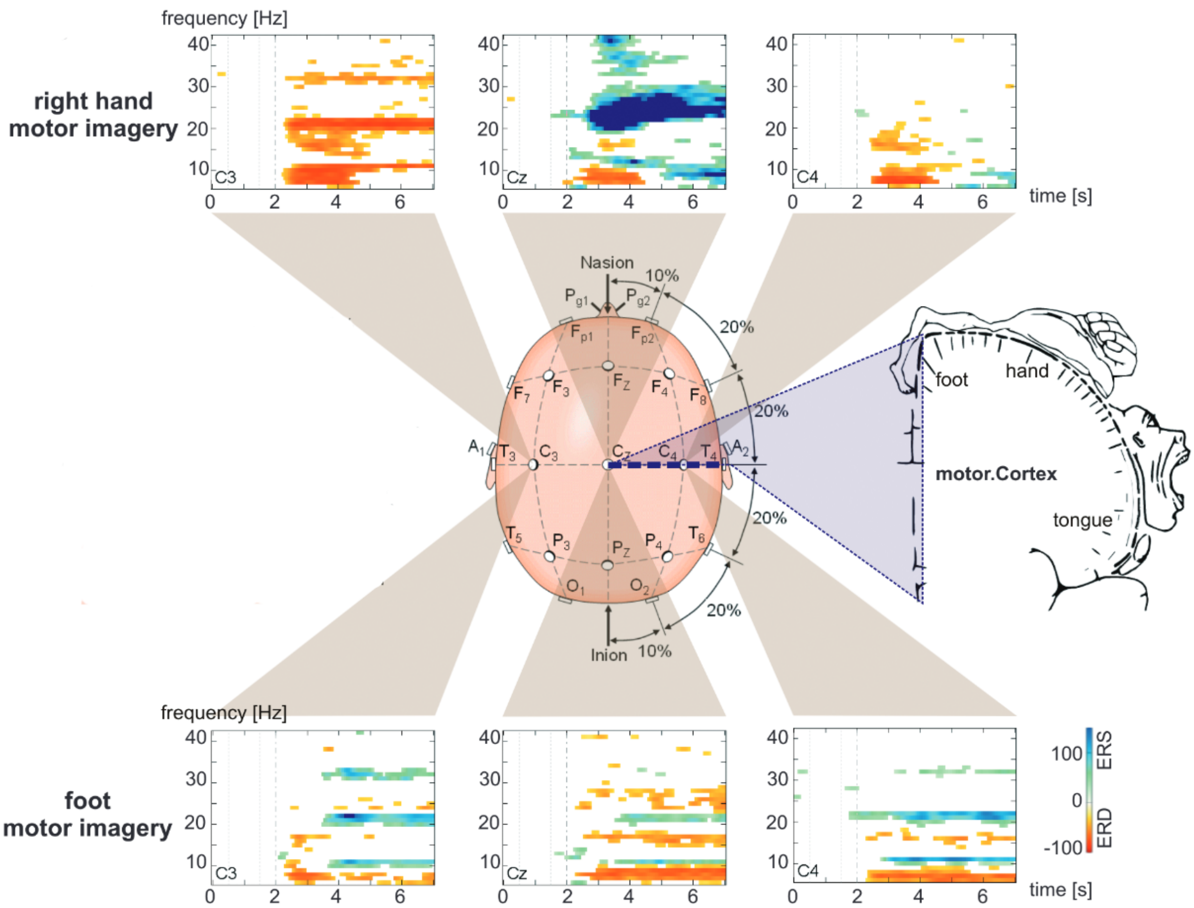
$$ers(f,t) = \frac{1}{n}\sum_{k=1}^{n} |F_k(f,t)|^2 \tag{2.1}$$

Where n is the number of trials, $F_k(f,t)$ is the spectral estimation of $k-th$ trial at frequency f and time t. The spectral estimation can be computed using either fast Fourier transform or Wavelet transform [Grandchamp and Delorme 2011]. ERSP measures the changes of the ERS/ERD activity as a function of the baseline, so each *ers* value at each time-frequency point per frequency band is divided by the average spectral power of the pre-stimulus baseline ($\mu_B(f)$) at the same frequency. Thus, the log-transformed ERSP is derived by:

$$ERSP_{log}(f,t) = 10\log_{10}(\frac{ers(f,t)}{\mu_B(f)}) \tag{2.2}$$

Thus, it is possible to obtain information regarding how synchronized the response is in comparison with the baseline at the same frequency. ERSP positive values represent ERS activity, whereas negative values ERD. This thesis uses ERSP to measure the ERD/ERS activity evoked by mental imagery tasks.

Figure 2.5 – Time-frequency maps (ERD/ERS) of the sensorymotor electrodes (C3, C4, Cz) during motor imagery tasks (rigth hand and foot).



Source: adapted from [Leeb et al. 2006]

More technical details about the methods and functions used in this thesis for the offline BCI system can be found in the chapter 4.

2.3 Virtual reality

Recently, immersive technologies have played an essential role in science, mainly in Human-Computer Interaction (HCI), where the user can experience alternative ways of communicating with machines. Among these technologies, Virtual Reality (VR) is one of the most promising technology, giving the users a sensation of full immersion in virtual world environments. VR creates a visual, auditory, and sometimes haptical, simulated experience of the physical world using a Head-Mounted display (HMD). This apparatus has an in-built high-definition screen in front of the eyes and several inertial sensors for tracking head movements to give the sensation of a first view. The primary objective behind this technology is to offer a sensory vividness of the virtual environment as closely as possible of a real one [Bohil, Alicea and Biocca 2011]. Figure 2.6 shows a traditional set-up of a VR experiment.

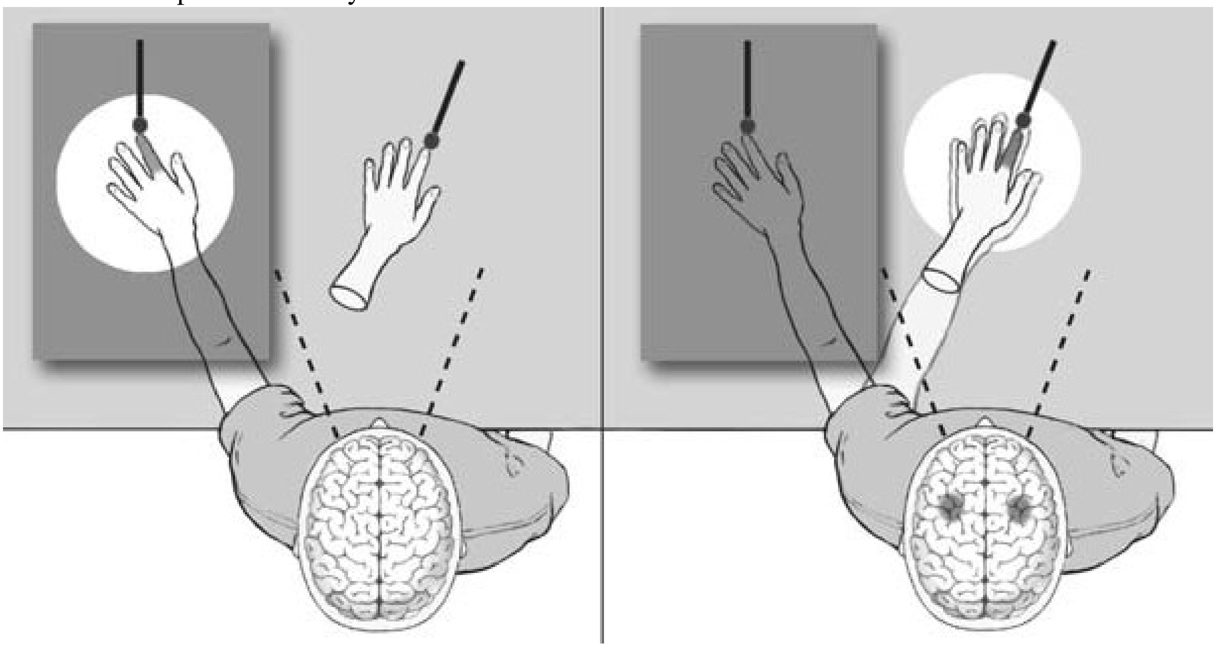
Figure 2.6 – Virtual reality set-up. a) the user wearing the HMD; b) an overview of the full VR scene; c) user's view in the VR world.

Source: adapted from [Pan et al. 2016]

Many applications have been made using VR, from health-care for rehabilitation and training [Schultheis and Rizzo 2001], up to education, data visualization and serious games [Gamito et al. 2017, Donalek et al. 2014]. Likewise, VR represents a powerful tool with graphical possibilities to improve the BCI feedback presentation. VR has successfully been used in different BCI scenarios. A. Lecuyer. et. al [Lecuyer et al. 2008] discuss some applications done using BCI in VR, namely MindBalance [Lalor et al. 2005], Simulation of wheelchair control [Leeb et al. 2007], and 'use the force' [Lotte, Renard and Lécuyer 2008]. These studies, as the authors highlighted, show the successfulness of VR using BCI. The next chapter discusses related works associated to the use of VR in BCI systems. This thesis uses a VR scenario for the training BCI. Chapter 4 details the experimental setup of the VR environment.

2.4 Body transfer illusion

Figure 2.7 – Rubber Hand Illusion (RHI) experiment. Left: experiment setup before the stimulus. Right: Both rubber hand and real hand are stroked synchronously and the user has the illusion of the rubber hand is part of the body.



Source: https://goo.gl/SJvutb

The human body is seen as the boundary between the external world and ourselves. One important concept in psychology is the sense of body ownership that human beings have, i.e. the usual experience that "my body" belongs to me [Gallagher 2000, Ferri et al. 2013]. Such experience relies on a multisensory integration of visual, touch and proprioception (body parts position) information.

However, an interesting experiment has captured the attention of the scientific community, mainly psychologists and neuroscientists. Botvinick and Cohen [Botvinick and Cohen 1998] found that subjects, after synchronous visual-tactile stimulation of a rubber hand and their hand, can feel the illusion of such artificial as part of the user's body. Figure 2.7 shows the setup of the experiment, the so-called Rubber Hand Illusion (RHI). Since then, RHI has widely been studied for researchers using different approaches such as a robotic hand [Romano et al. 2015], BCI system [Perez-Marcos, Slater and Sanchez-Vives 2009], and VR scenario [Slater et al. 2008]. Indeed, VR is seen as a powerful tool to create a body illusion if appropriate multisensory correlations are provided [Slater et al. 2008].

This thesis aims to create a body transfer illusion, like the RHI, using a third arm in VR in order to study the implementation of a supernumerary BCI system.

2.5 Cognitive load

Finally, an important concept related to how hard the task is for the user is described in this section. Cognitive load describes the mental resources used by a human operator for performing a particular task [Sweller 2011]. In effect, Working Memory (WM) is responsible for briefly maintaining sensory information and processing it in order to perform cognitive tasks (making decisions, reading, making logical operations) [Cowan 2008]. Since that Working Memory Capacity (WMC) is limited, the amount of information to be processed can affect the user's performance; therefore, it is mandatory to include the cognitive load in the development of task or interfaces.

Several researchers have suggested different approaches to measure the cognitive load. They can be divided into subjective and objective measures [Charles and Nixon 2019].

2.5.1 Subjective measures

The most typical subjective technique to measure cognitive load is the NASA-TLX (Task Load Index) [Hart and Stavenland 1988], which provides a six-dimensional rate of workload to finally obtain an overall workload. These dimensions consist of different factors about completing a task. NASA-TLX is composed for the next rating scale questions:

- How much mental and perceptual activity was required? (Mental demands).
- How much was physical activity required? (Physical demands).
- How much time pressure occurred? (Temporal demands).
- How successful do you think you were in accomplishing the goals of the task set by the experimenter? (Performance).
- How hard did you have to work –mentally and physically- to accomplish your level of performance? (Effort).
- How insecure, discouraged, irritated, stressed versus secure, content and relaxed did you feel during the tasks? (Frustration level).

Moreover, a binary selection between demands (which demand was more important?). Even though the NASA-TLX yields a useful summary about the complexity level of the tasks for the users, it cannot give ongoing information about the current state of the user performing the task; Also, the limitation of NASA is that only can be made once per task. Even so, Hart [Hart 2006] points out that the NASA-TLX is very useful to evaluate the interface design. Besides, task metrics can also be used to assess the cognitive load. Reaction Time (RT) and Error Rates (ER) are two common variables for evaluating the user's performance. Thus, as longer RT and higher ER, a higher cognitive load is experimented by the user [Charles and Nixon 2019].

2.5.2 Objective measures

In the other hand, objective measures use sensors for monitoring the cognitive load. Electrodermal activity (EDA), eye movements and pupil size, heart rate variability, and EEG are the most used measurement methods [Charles and Nixon 2019]. Using EEG, several researchers have reported that alpha, beta and theta activity is related to cognitive load in several tasks demands [Antonenko et al. 2010]. In effect, Alan Gevins and Michael E. Smith [Smith et al. 2001] found that the power changes of θ at frontal mid-line sites and α at parietal sites are related to the task load associated to the mental effort required for task performance. Thus, they proposed Task Load index in order to have an objective measure of the cognitive load produced by a specific task.

This thesis uses the Task Load Index proposed by Smith and Gevins for monitoring the ongoing cognitive load during the different mental imagery task. Besides,following the work done by Felton and colleagues [Felton et al. 2012], NASA-TLX (see Appendix C) is used for assessing the cognitive load of the training setup.

3 RELATED WORK

This chapter introduces related works that were fundamental in the conception of this thesis. Mainly, these works are grouped following the three topics of this work and their relation with BCI: Motor Imagery, Virtual Reality, and Rubber-Hand Illusion.

3.1 Motor Imagery Brain-Computer Interface

Since the activation patterns of imaginary body movements involves both brain regions (sensory and motor areas) and neural mechanisms similar to the executed movement [Jeannerod 1995], the Motor Imagery BCI (MI-BCI) has been widely used and explored method for communication and controlling of devices using the electrical brain signals (EEG) [Wolpaw et al. 2002]. MI-BCI employs the amplitude changes voluntarily elicited by the mental representation of physical motor actions (ERD/ERS). These patterns have been successfully used for studying the neural mechanisms associated with motor actions, as well as a feature for classification in motor-related BCI systems [Pfurtscheller and Neuper 2001, Wolpaw et al. 2002, Gert et al. 2011, Neuper et al. 2003]. BCI plays an important role in HCI due to its countless applications; ranging from clinical implementations, supporting the rehabilitation of motor-impairment patients [Neuper et al. 2003], up to controlling mobile robots and games [Bi, Fan and Liu 2013, Gert et al. 2011].

However, despite BCI being a promising and useful application, there are still several challenges to be addressed. Chavarriaga et al. [Chavarriaga et al. 2017] discuss concrete research avenues and guidelines to overcome common pitfalls in BCI. Their paper is the outcome of a meeting held at the workshop “What’s wrong with us? Roadblocks and pitfalls in designing BCI applications”. They summarize four main topics that influence any closed-loop BCI system: *a*) End Users; *b*) Feedback and user training; *c*) Signal processing and decoding; and *d*) Performance metrics and reporting.

The fast growth of machine learning and unsupervised systems (i.e. deep learning) have supported the signal processing of EEG data and consequently, BCI systems [Lotte et al. 2018]. As BCI is a relatively new research area, establishing metrics to objectively asses BCI systems (e.g., classification accuracy plus usability) is still a task to be done. Potential user identification is a mandatory step to design suitable BCI applications. However, this requires additional resources and developments of wearable recording equipment. Finally, the training and feedback should consider human factors and include the user inside the BCI loop through a more realistic, natural and intuitive training and feedback. This thesis focuses on two of theses avenues: Feedback and user training, and Signal processing and decoding.

For the first one, researchers, along the years, have widely used the Graz BCI feedback and training paradigm for MI-BCI applications [Pfurtscheller and Neuper 2001]. In this standard, subjects have to imagine either right or left-hand movement following an arrow cue and watch a horizontal bar as feedback that is extended based on the classifier’s accuracy. Likewise, different feedback presentation has been proposed following the same paradigm such as a falling ball [Blankertz et al. 2007], visual cursor and auditory feedback based on the subject’s sensorimotor rhythms [Nijboer et al. 2008], and tactile feedback in the corresponding arm classified [Chatterjee et al. 2007]. Usually, all of these applications are computer screen-based, and the feedback does not congruently represent the imaginary task (motor imagery) [Alimardani, Nishio and Ishiguro 2018]. Here, VR techniques address these limitations, using realistic and motivated feedback applications. The next section discusses VR approaches in BCI.

Meanwhile, in the literature, comparisons and reviews of the different feature extraction methods and classifiers for MI-BCI have been performed. Firstly, Lotte [Lotte 2014] made a signal processing tutorial for recognizing mental states, suggesting that spectral and spatial information is commonly used for feature extraction in MI-BCI, mainly the band power of specific frequency rhythms and Common-Spatial Patterns (CSP). Moreover, Chaudhari and Galiyawala [Chaudhari and Galiyawala 2017] as well as Lotte and colleagues [Lotte et al. 2007], made a systematic review of classifiers for BCI systems, showing that in MI-BCI, Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) are the most used linear classifiers, meanwhile, K-Nearest Neighbor (KNN) and Artificial Neural Networks (ANNs) are widely used in multiclass classification. In another hand, Resalat and Saba [Resalat and Saba 2016] studied several methods for extracting features in MI-BCI systems using LDA as the classifier. They found that spectral methods and Auto-Regressive (AR) have higher accuracy rates. However, they only used one classifier, which could be insufficient for concluding the best technique. In another side, Bashashati et al. [Bashashati et al. 2015] explored the accuracy of several classifiers for a specific feature extraction method (CSP), showing that Logistic Regression (LR) and ANNs obtained higher accuracies. However, the authors emphasized that the best combination of classifier, feature and model parameters should be selected for each subject since that BCI is an user-dependent system. In such vein, this thesis proposes to create a framework for comparing different frequency bands and time windows for extracting spatial features (CSP), and several classifiers (SVM, KNN, LDA) in order to choose the best combination of features and classifier for each user per task. Chapter 4 gives a detailed explanation with the technical details of each method used.

3.2 Virtual Reality and Brain-Computer Interface

Virtual Reality is a powerful tool for improving BCI training and enhancing feedback experiences [Neuper and Pfurtscheller 2010]. Training tasks should include an intuitive presentation so that the users can easily understand the action to be executed and improve their performance. However, it is currently hard to choose the right presentation, and it should be a motivating and engaging environment, as it is pointed out by [Chavarriaga et al. 2017], besides natural and realistic. Here, VR can be shown as a real alternative for tackling this presentation issue.

Lotte et al. [Lotte et al. 2013] show how combining BCI with VR can carry towards a new and improved BCI system. Nevertheless, such VR feedback can also introduce some interference to the motor imagery-related brain activity used by the BCI because both μ and β bands are reactive in motor imagery and observation of the real movement [Pfurtscheller and Neuper 2001]. An interesting study carried out by Neuper et al. [Neuper et al. 2009] explores the influence of different types of visual feedback in the modulation of the EEG signal during the BCI control. Using a video to show a first-person view of an object-directed grasping movement, they were able to found modulation activity in sensorimotor rhythms caused by this real feedback stimuli. They highlight the importance of the amount of information provided by this condition in order to reduce the reactive bands.

Likewise, Ron-Angevin and Diaz-Estrella [Ron-Angevin and Diaz-Estrella 2009] made a comparison between the screen condition (Graz) and VR, focusing on the BCI's performance (classification rates). They successfully found improvements in the feedback control of the VR condition in untrained subjects. However, they used car navigation as a task, which could be seen as an abstract object because it is expected natural and realistic feedback, such as an arm doing the imaginary task performed by the user. So far, all of the studies cited above have used different feedback stimuli, but none of them has used a virtual arm, which could be useful for the training step.

Precisely, Skola and Liarnokapis [Skola and Liarokapis 2018] carried out a recent work using an embodied VR training for MI-BCI. A human-like avatar performs the motor actions in synchrony with the user's actions. This neurofeedback-guided motor imagery training reports improvements in classification rates in comparison with the Graz paradigm. Even though it was not reached a significant difference, the authors report that ERD in VR subjects is stronger than the control group. Likewise, the same sort of results is reported by Braun et al. [Braun et al. 2016]. However, in this case, an anthropomorphic robotic hand is used as a visual guide. Also, they found differences between the two conditions in the electrodermal activity and subjective measures. Thus, this thesis aims to study the advantages presented by a realistic VR scenario adopting a realistic arm as a training application, in comparison to the traditional Graz scenario (arrows and fixation cross). Both training conditions were made in a VR environment.

3.3 Body transfer illusion and Brain-Computer Interface

So far, MI-BCI applications have used attached body parts, in other words, mental representations of jointed limbs following the human anatomy constraints (e.g., two arms, two legs, two feet, in a symmetrical distribution). To the date, nevertheless, there is neither explorations nor applications that include non-embodied human limbs, although the RHI experiments demonstrated the human capabilities to create body transfer illusions [Botvinick and Cohen 1998, Ferri et al. 2013]. Indeed, the RHI demonstrates not only a static body illusion representation (sense of ownership) but also an active movement eliciting a body illusion (sense of agency) [Kalckert and Ehrsson 2012].

In the works of Braun et al [Braun et al. 2016], and Skola and Liarnokapis [Skola and Liarokapis 2018] reported that they were inspired by the RHI experiment. They also include within their discussions, the analysis of the sense of ownership, agency, and self-location towards the non-body object, concepts that are being recently taken into account in BCI research [Alimardani, Nishio and Ishiguro 2016, Alimardani, Nishio and Ishiguro 2014]. Nevertheless, there is not any substantial effort to study and explore the possibility of using the RHI as a control command inside the BCI loop, creating thus a supernumerary limbs BCI system.

Bashford and Mehring [Bashford and Mehring 2016] proposed this possibility with their work. They used an imaginary third arm for assessing the ownership and agency of a non-body limb in an imitation BCI (i.e., subjects think that their EEG activity is controlling the arm).

Results show that there is independent ownership and control – based on the correct movements observed against the subject movements – of the third arm keeping the sense of ownership of the real hands. These findings suggest the capabilities of human of extrapolating limbs to execute motor actions. However, they did not study the use of this third arm as a control command inside the BCI loop. Moreover, Perez-Marcos and colleagues [Perez-Marcos, Slater and Sanchez-Vives 2009] used BCI for inducing a virtual hand illusion ownership. The authors use MI-BCI for controlling the movements of the third virtual arm and found correlations between the muscle activity and movements of the virtual arm. However, they used attached body parts (left hand or right foot movements) to elicit the control signals, rather than a third virtual arm. This thesis aims to study the inclusion of a third virtual arm (emerging from the chest) to elicit an RHI, but also this work explores the classification of this arm from the left and right-hand movements in order to use it in an MI-BCI system. This thesis is a step towards the developing of a system using MI-BCI for supernumerary limbs by performing a study on the ability to control a third imaginary arm, while comparing the effectiveness of using the conventional arrows and fixation cross as training step (*Graz*) against a first-person view using a human avatar (*Hands*).

4 MATERIALS AND METHODS

4.1 Overview

An offline MI-BCI experiment, which uses EEG for recording the data and VR scenarios for presenting the stimulus, was conducted in a reduced noise room. The experiment's aim is to check the feasibility of controlling a virtual third arm using MI-BCI while the traditional training paradigm (Graz) is compared against a first-person view using a human avatar. There were two recording sessions with two runs in each one with a resting time between them. The sessions were conducted on two separate days within one week. Only on the first day, the participants had to fill up three questionnaires: MIQ-3 (see Appendix A), demographics and Edinburgh Handedness (see Appendix B). Likewise, after each session, participants filled the NASA-TLX form (see Appendix C).

4.2 Participants

Ten right-handed volunteers (four women) participated in the study. Participant ages were within 18 and 34 years old with a mean of 23. All participants had basic informatics knowledge. Only 30% did not have previous experience with VR and no one had any previous experience in MI-BCI. No one had problems with the head movements. Half of the population had visual impairments (mainly myopia and astigmatism). The experiment was conducted in accordance with the Declaration of Helsinki. Participants were informed both oral and written about the procedure and the EEG recording. All participants gave written informed consent (see Appendix B).

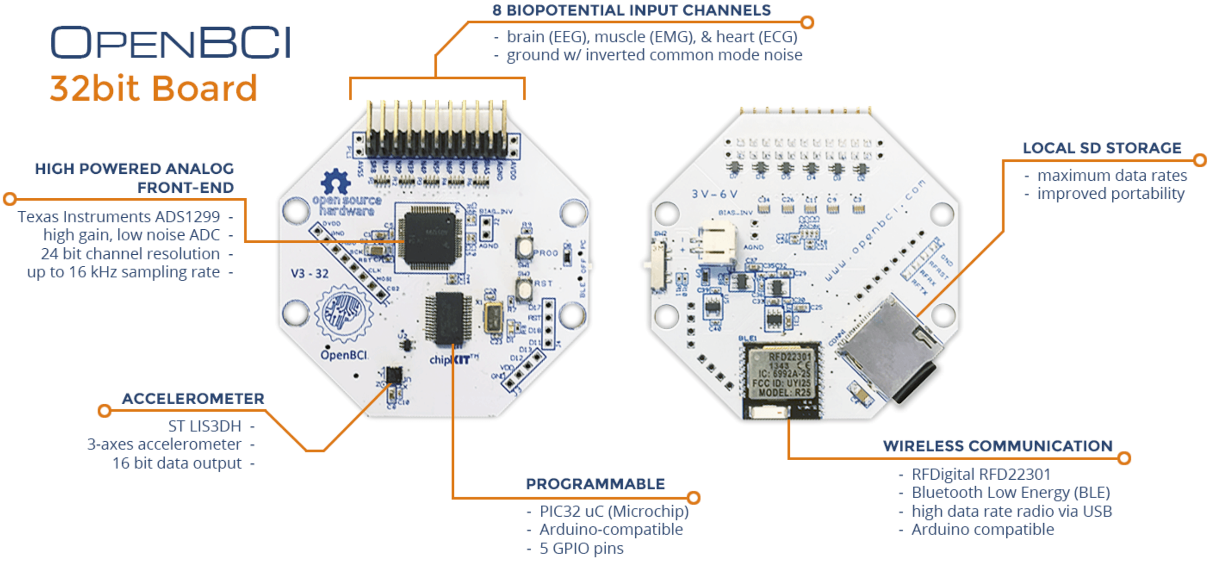
4.3 Data Acquisition

The EEG data was collected using an OpenBCI 32 bit board at a sampling rate of 250 Hz. It is an Open Source Arduino-compatible component that can be used to measure the brain activity (EEG), heart activity (EKG) and muscle activity (EMG). Figure 4.1 shows and describes the features of the Open BCI board [BCI 2019]. Following the 10-20 EEG placement system, eight passive gold cup electrodes were used and placed at sensorimotor cortex (see right side of Figure 4.2), namely, frontal (F3, Fz, F4,) central (C3, Cz, C4), and parietal (P4, P3) cortices. Left and right mastoids were used as reference and ground electrodes respectively.

For the VR exposition, a head-mounted display (HMD) Oculus Rift CV1 is used with a resolution of 2160 x 1200 (1080 x 1200 per eye), refresh rate of 90 Hz, a 110^{o} field of view, and both rotational and positional tracking for delivery the immersive scene. The popular game engine Unity3D was used to develop the immersive scene that was intended to assist the user when imagining and performing motor actions whit their arms, left and right real arms and the middle imaginary one (see left side Figure 4.2).

There was a special focus on the realism of the models: left and right hands were placed matching with the rest positions of the real hands. A third hand was placed in the middle of the

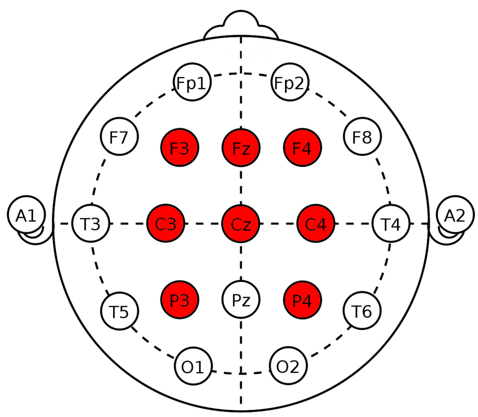
Figure 4.1 – Open BCI board and its main features.



Source: https://goo.gl/iDSi9v

body, like emerging from the chest trying to avoid visual relations with the left or the right arm. The fingers on the third arm also were modified to be symmetric, since that the thumbs in either left and right hand can indicate to which arm it belongs, their were removed from the third arm. In this way, it is ensured an independent arm and not a copy or extension of the existing arms. High-quality textures were used with shaders designed to highlight generic skin details. Bones in each finger preserve the average human hand proportions.

Figure 4.2 – Experiment setup. Left: A subject using a BCI interface to control his “three” arms in a virtual reality experience. Right: the electrodes placement over the sensorimotor area (filled circle), following the 10-20 system.



Source: the author

In order to synchronize the EEG data and the markers that indicate when a specific task started, the lab streaming layer (LSL) library [Boulay 2019] is used for recording experimental data. LSL is an open-source system that unifies different time series collected in research experiments, offering a centralized collection with near real-time synchronization (sub-millisecond accuracy on local network) based on Network Time Protocol (NTP). The recorded streams are compiled into a XDF file format (extensible data format) which supports a multistream container data, large headers, and sample and time-synchronization information). The EEG data is labeled with the Unity trials using LSL4Unity (a third party software based on LSL) [xfleckx 2019].

4.4 Experimental Procedure

The experiment involves the execution of four different task in two experimental conditions. The subjects were invited to rest (RS), or to move a specific hand: third hand (TH), left hand (LH), and right hand (RH). Conditions considered were: *Graz*, and *Hands*. The *Hands* condition involved the presentation of a human-like avatar, whereas *Graz* the presentation of arrows.

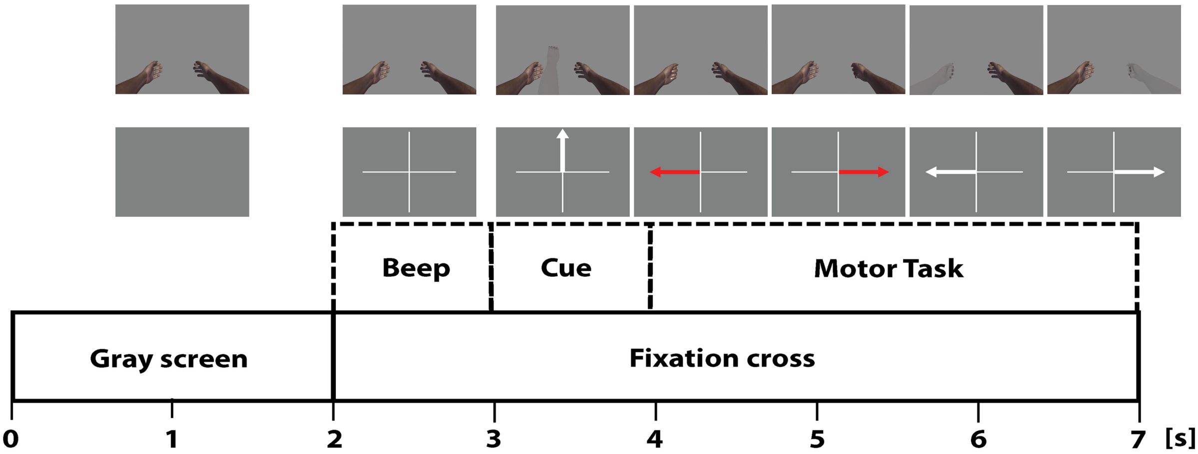
The subjects sat comfortably in an armchair and were asked to rest their arms in the armrest and avoid any other movements during the recordings. Initially, the participants wore the HMD for getting into the scene and running several trials for learning the instructions previously read. After the training, the EEG cap is mounted, followed by the traditional gelling process, and then the HMD is fit, trying as much as possible to avoid that the HMD frame touches the EEG electrodes. Moreover, the signal quality is checked before and after mounting the HMD.

The two experimental conditions followed the timing protocol proposed by Pfurtscheller [Pfurtscheller and Neuper 2001]. The users performed 20 trials of each task (randomly selected) with a duration of 7 seconds (see the bottom side of Figure 4.3). The main difference between the conditions lies in the visual feedback, as follows:

1. *Graz* condition: starting with a gray screen (resting state), at time 2s, a fixation cross at the center of the scene was displayed with a short warning tone ('beep') which indicates to the user to pay attention to the incoming visual cue presented at time 3s. At time 4s, the user had to perform the motor task for three seconds. The color of the arrows indicates the task (red for execution and white for imagination) and its direction indicates if the hand should be either left or right. The third arm cue was an arrow pointing upwards (see the middle of Figure 4.3).

2. *Hands* condition: at the start, the user's hands were placed in the equivalent real arms positions (resting state), at time 2s, the same auditory cue starts indicating an incoming stimulus. Next at time 3s, a visual cue is introduced without animation to let the user prepare for the action they will. At time 4s, the animation is introduced, and the user must perform either the mechanic or imaginary operation. This state continues until the end of the task (three sec more). For the visual cues, the real skin shading represents actual open-close hand movements, while transparent shading represent imaginary movements. Moreover, it is important to highlight that the third arm appears in the scene only when this specific trial is necessary. In other trials, there are just two visible hands (see the top of Figure 4.3).

Figure 4.3 – Experiment paradigm. The visual stimulus of the task's cue are corresponding for both experimental conditions. Top: visual stimuli for *Hands* condition. Middle: visual stimuli for *Graz* condition. Bottom: timing of the trials following the classical Graz protocol.



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Following [Neuper et al. 2005], subjects were instructed to perform the kinesthetic experience in motor imagery tasks, i.e., imagining the sensation of performing the motor tasks rather than the visual representation of the movement. The authors suggest that kinesthetic motor imagery is essential to elicit sensorimotor patterns (ERD\S). Besides, in order to avoid the carry-over bias, both experimental conditions were counterbalanced across participants (i.e. five subjects start with *Hands* condition and the rest with *Graz*). Likewise, it is necessary to mention that the movement animations were applied directly to the bones always looking for a natural behavior of the hand. The animations are predefined, they are not based on the user's EEG activity.

Finally, in contrast to Skola and Liarnokapis [Skola and Liarokapis 2018] where the *Graz* condition is presented in a monitor, this thesis performs comparisons of the *Graz* and *Hands* conditions in a virtual environment. Therefore, the users have to wear the HMD in both conditions. The background of Graz scenario was set to gray, avoiding high contrast that could produce discomfort on the user's eyes.

4.5 BCI pipeline

4.5.1 EEG pre-processing

The recorded data is imported and processed into EEGLAB (14.1) [Delorme and Makeig 2004] (under Matlab 2017b). After down-sampling at 115 Hz, the signals are band-pass filtered at range 1-35Hz using a finite impulse response (FIR) filter. Usually, a notch filter is used for line noise, but this method generally creates band-holes, and distortions close the cut-off frequency. Therefore, the Cleanline plugin, which uses multi-taper regression for removing sinusoidal artifacts, is used at 50-115 Hz instead. Likewise, Cleanraw plugin is set-up for rejecting bad channel, no more than two (mainly the sensormitor ones). The rejected channels are then interpolated using a spherical function. Finally, EEG signals are re-referenced using common average referenced (CAR).

As this thesis aims to explore the featuring extraction and classification of the third virtual arm in an MI-BCI, an extension of the CSP method is used for extracting discriminative patterns from both temporal-spatial EEG features. This approach, known as Filter Bank Common Spatial Pattern (FBCSP) [Ang et al. 2008], uses CSP in several frequency bands and runs a feature selection algorithm to automatically choose the relevant frequency bands and their corresponding CSP features. Therefore, to study, as much as possible, the influence of both time window of the trials and the frequency bands on the accuracy of the classifiers, this thesis uses FBCSP algorithm for several time windows (100, 200, 400, 600, 800, 1000 and 2000 *ms*) for extracting features and evaluating the classification accuracy. The bank with the MI frequency bands is comprised of alpha (8-12 Hz), low beta (12-16 Hz), middle beta (16-24 Hz), high beta (24-30 Hz), and whole beta (12-30 Hz) bands. The reason for splitting the beta band into sub-bands is for getting enough variables for the FBCSP algorithm to work. The next section explains FBCSP method and the proposed framework.

4.5.2 Feature extraction

The ERS/ERD patterns are predominant in alpha (8-12 Hz), and beta (13-30 Hz) rhythms and their onset go from 500ms up to three seconds after the movement execution [Pfurtscheller 1999]. Inspired by these facts, this thesis creates a framework to obtain the best combination of window size, frequency band, and classifier for each user. Obtaining a pool of all possible combinations, running the FBCSP algorithm [Ang et al. 2008] in seven time-window sizes of the signal (100, 200, 400, 600, 800, 1000 and 2000 *ms* onset the stimuli) and five frequency bands (8-12 Hz,12-16 Hz, 16-24 Hz,24-30 Hz,12-30 Hz). The method employs a greedy algorithm to heuristically find the best combination based on the classification error rates (validation) of all possibilities. Focusing on the variability that exists across the users in their performance, this approach proposes to create a suitable and user-centered offline BCI classification.

The FBCSP approach has demonstrated successful performance in BCI applications [Ang et al. 2008]. Likewise, CSP is one of the most known and widely used methods for extracting features in a two classes BCI application [Blankertz et al. 2008,Lotte 2014]. CSP computes the project matrix $\mathbf{W} \in \mathbb{R}^{c \times c}$ that linearly transforms the band-pass filtered data $\mathbf{E} \in \mathbb{R}^{c \times t}$ into a spatial filtered signal $\mathbf{Z} \in \mathbb{R}^{c \times t}$ (with c being the number of channels and t the EEG samples per channel) as follows:

$$\mathbf{Z} = W^T E \tag{4.1}$$

Thus, the power of $\mathbf{Z}$ effectively discriminates two mental states (classes), maximizing the variance under one condition; meanwhile, it is minimizing for the other [Blankertz et al. 2008]. In order to get the most discriminative patterns, the first and last m (m=3) columns of $\mathbf{W}$ were used to create the spatial-filtered signal $\mathbf{Z}$. The m-dimensional feature vector is then formed from the logarithm of the normalized variance of $\mathbf{Z}$:

$$v_i = \log(var(Z_i)), \quad i = 1, 2, ..., 2m. \tag{4.2}$$

This results in 30 features (six CSP filters per each frequency bands) for each EEG trial in the specific window. From these features, the maximum Relevance Minimum Redundancy (mRMR) feature selection algorithm is used to extract the most relevant features [Peng, Long and Ding 2005]. This algorithm minimizes the redundancy meanwhile maximize the relevance of the features using mutual information. As the size of v_i depends on the frequency bands, the number of selected features was progressively increased (step = 3) from the minimum amount (6) up to the total size of v_i. Hence, the selected features for each time window is used to separately train three BCI classifiers [Lotte et al. 2007]: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA).

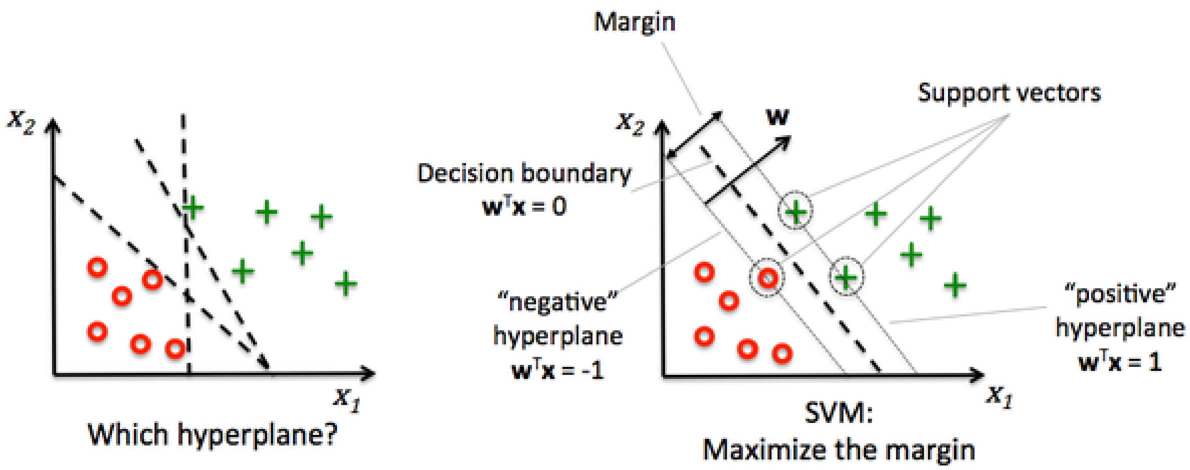
4.5.3 Classification

Linear classifiers have successfully demonstrated their excellent performance in BCI applications due to their simplicity and processing time [Lotte et al. 2007]. Moreover, non-linear classifiers offer to map the input data into higher dimensional space where the classes are easily separable. Therefore, this thesis uses two of the most popular linear approaches (SVM and LDA) and a non-parametric method (KNN).

SVM is one of the most known supervised method for learning. SVM finds the optimal hyperplane that separates the data by maximizing the margin between the classes. The original SVM can easily be extended to a non-linear method using the kernel functions $K(x,y)$. Meanwhile, LDA obtains the hyperplane by the projection of the covariance matrices that maximizes the distance between the classes means and minimizes the inter-class variance. The figure 4.4 shows the main differences between the two classifiers visually, as it was explained before, it lies in the way how the hyperplane is calculated. Both SVM and LDA uses the same equation of the hyperplane as well as a sign function for predicting the labels. The hyperplane is defined by:

$$y = w^T x + b \tag{4.3}$$

Figure 4.4 – Linear classifiers. Left: Linear Discriminant Analysis (LDA). Right: Support Vector Machine (SVM).



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In the other hand, KNN is a non-parametric method that assigns the class label by calculating the distances between the incoming data and a set of k nearest training data. Such distance is measured with several methods, where the Euclidean distance is the most used [Mitchell 1997]. This distance function (D) is described by:

$$D = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{4.4}$$

These methods were trained to classify independently four binary imaginary tasks: Third and Left hand (TH\LH); Third and Right hand (TH\RH); Third hand and Resting State (TH\RS); and Left and Right hand (LH\RH). The data of each run is merged into a single dataset for thus training the classifiers. The reader can notice that the real movements are not included in the classification. The intention of including the real movements in the experiment was to reduce the abstractness of the three imaginative tasks and have a fresh mental representation of the action.

The miss-classification error was computed using the usual k-fold cross-validation approach. This method randomly divides the filtered data into k equal size partitions and uses k-1 sets to train the model and one set to validate it. In this study, we used ten times the 10-fold cross-validation. Finally, the above classifiers were implemented using the Statistics and Machine Learning Toolbox of Matlab. Both SVM and LDA used the default parameters (linear kernel, C=100, and standardize predictor data for SVM and LDA without any hyperparameter optimization). KNN uses a Euclidean distance and $k = 5$.

4.6 Event-Related Spectral Perturbation (ERSP)

The event-related spectral perturbation (ERSP) is a generalization of the ERD/ERS patterns. ERSP computes the changes of the spectral powers in time-frequency domains, relative to the stimuli [Delorme and Makeig 2004]. Thus, with this approach, the changes of the EEG signals elicited by motor imagery events can be detected alongside the spectral band and epoch. ERSP values were computed for every mental task (TH, LH, RH, RS) in *Graz* and *Hands* conditions using the *newtime* function of the toolbox, which uses FFT with a Hanning window to remove window border effects. The function uses a time window of -500 ms to 2500 ms across the frequency range of 5 to 30 Hz for 200 output times. The Bootstat function was set up with a significant alpha of 0.05 for calculating the two-tailed permutation significance probability. The sensorimotor area composed by the electrodes C3, Cz and C4 were used to display the time-frequency ERD/ERS maps (See Figures 5.1 and 5.2 in the Chapter 5).

4.7 Task load index

Task load index developed by Alan Gevins and Michael E. Smith [Smith et al. 2001] is used in order to have an objective measure of the task load. The authors found that the power changes of θ at frontal mid-line sites and α at parietal sites are related to the task load associated with the mental effort required for task performance. Thus, this index can be measured by the ratio of θ to α. In this thesis, besides of the subjective assessment of the cognitive load by the NASA-TLX [Hart and Stavenland 1988], the average of the absolute power of frontal mid-line (F3, Fz, F4) θ and parietal (P3-P4 plus Cz) α were used to assess the mental tasks per condition (*Graz* and *Hands*).

5 EEG ANALYSIS

5.1 Summary

This chapter presents and discusses the EEG patterns found for the three imaginary tasks (TH, LH, RH) using ERSP method. ERD/ERS maps are shown in order to describe the EEG activity during the execution of the tasks in a time-frequency representation. These maps reveal strong and widespread ERS patterns for the third arm in both conditions as well as that the realistic training (*Hands*) elicits stronger ERS/ERD activity than the traditional Graz condition. Furthermore, the power changes analysis complements the above findings since that the *Hands* conditions presents more significant regions than Graz conditions (mainly at C3 than the other locations), where the power difference is clearly perceived.

5.2 Results

5.2.1 ERSP results

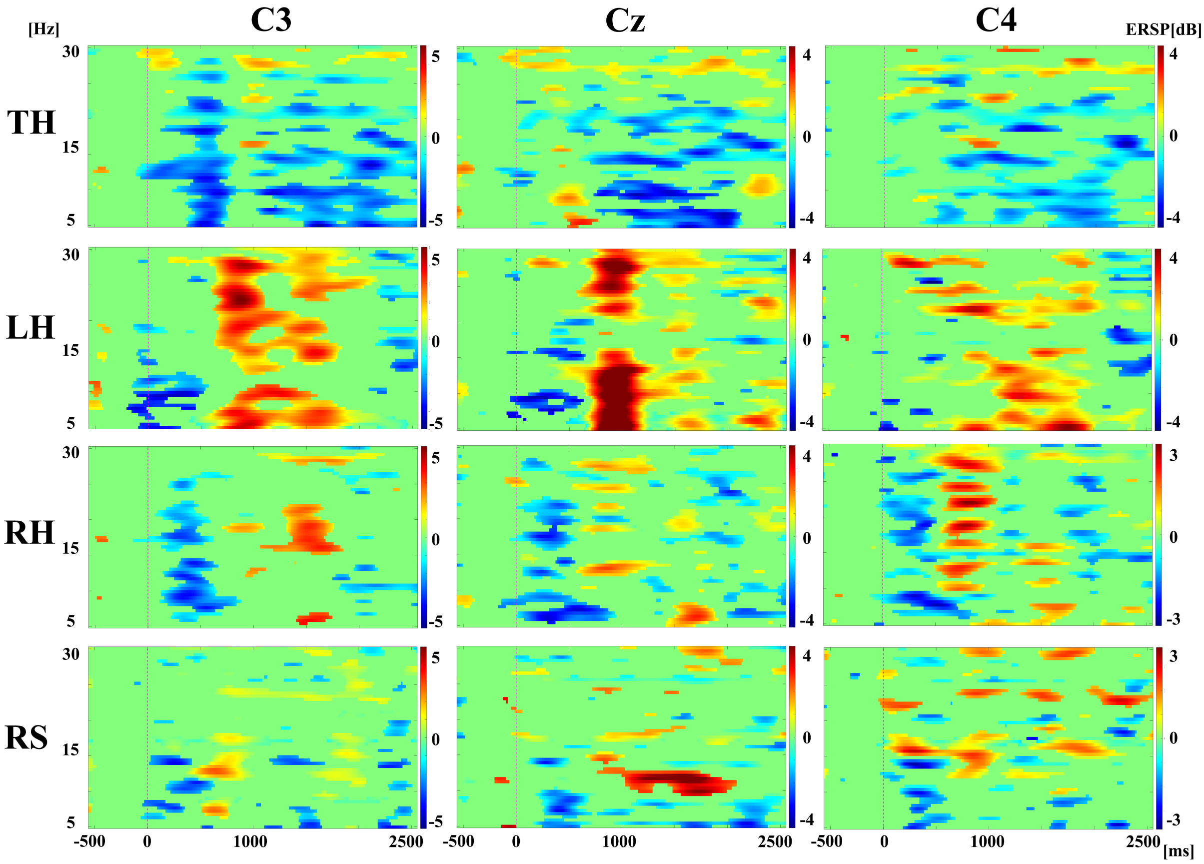
Figures 5.1 and 5.2 show the time-frequency representation of significant (bootstrap method, $p < 0.05$) ERD/ERS values (blue indicates ERD) for the Hands and Graz condition respectively. These maps coming from a single subject (*6*) at electrode positions C3, Cz and C4. The subject was chosen because it has reached the lowest classification errors (see the next chapter).

For the TH task, at C3 position in Hands condition, a strong power decrease is clearly visible around 500ms after stimulus onset, and this behavior is presented in almost the whole frequency range; whereas in the other two imagery tasks, LH has a decrease in alpha followed by an increase in alpha and beta; RH has a similar pattern but without ERS activity in alpha. Interestingly, TH task held the ERD activity during the rest of the epoch after 1000ms with few ERS in middle and high beta band. Conversely, in Graz condition at C3, the ERD patterns of the TH task are attenuated and widespread with some ERS activity at the end of the epoch in high beta band.

At Cz in Hands condition, the TH task presents an ERS activity that starts around 500ms in alpha, and an ERD that starts around 1000ms in alpha and beta band. LH presents a strong ERS activity in both alpha and beta anticipated by an ERD in alpha and middle beta. RH has a strong ERD activity in alpha and beta and posteriorly some ERS in beta. Meanwhile, in Graz condition, TH shows ERD pattern in alpha until the first 1000ms At the end of the epoch, some ERS activity is presented in high beta. In LH, there is an ERD pattern in alpha during the first 500ms and a widespread ERS activity later. RH holds the ERD in alpha at the same time with some ERS in middle beta.

Similarly, TH task in Hands condition presents an ERD pattern around 500ms in alpha and middle beta at the C4 position. This activity is held again during the whole epoch (mainly in alpha). Few ERS activity is found in high beta after 1000ms. The ERS activity is most prominent in alpha and low-middle beta for LH, meanwhile, RH shows an ERD/ERS pattern

Figure 5.1 – Significant ERD/ERS patterns of the mental task at C3, Cz, C4 positions for Hands condition. A strong ERD activity is found at the three electrodes for the third hand (TH). Whereas, ERS patterns are found mainly for the left hand (LH). The ERD/ERS fluctuation is more visible for the right hand (RH), mostly at C4.



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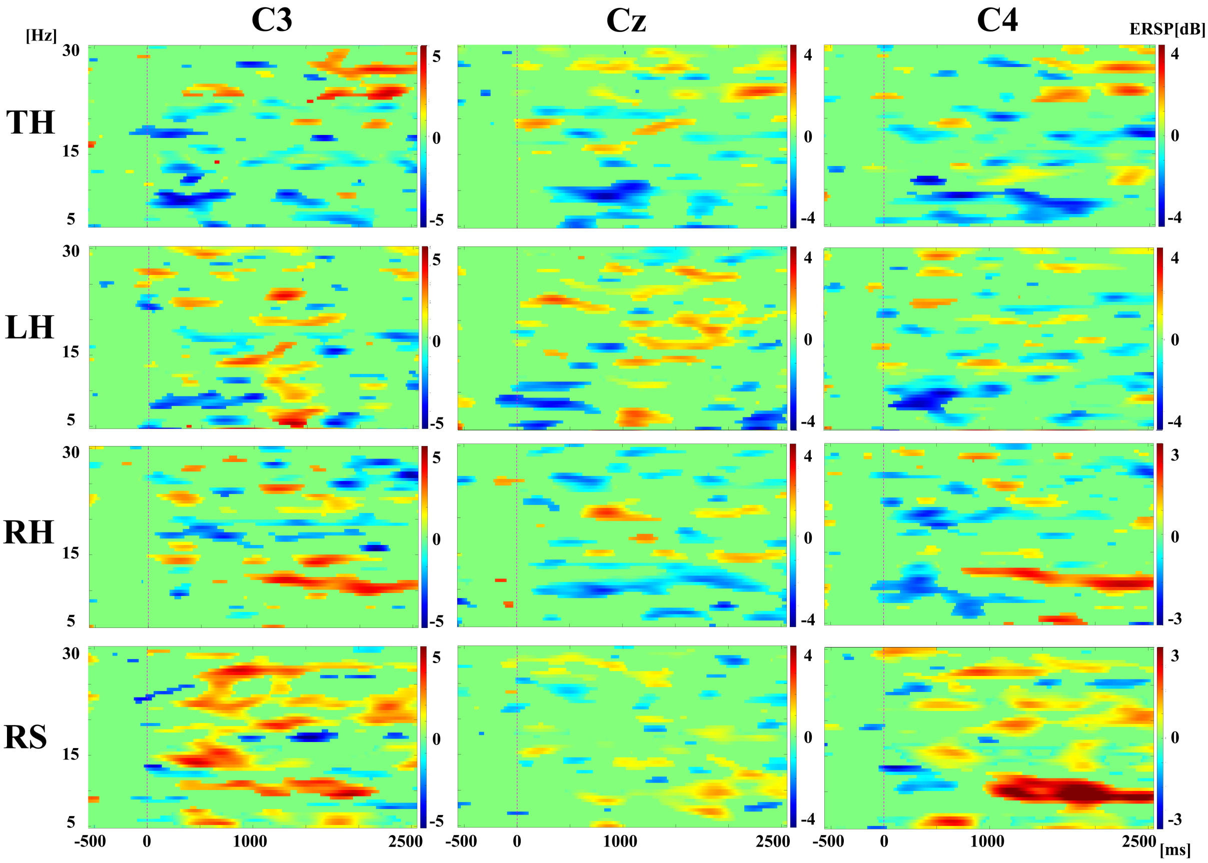
in alpha and beta in the first 1000ms. For Graz condition, the ERD patterns of TH task are widespread in alpha and beta between 500ms and 1500ms with some presence of ERS in high beta. LH has a strong ERD activity during the first 1000ms in alpha and some widespread ERS in high beta. RH has strong ERD patterns during the same previous time in both alpha and middle beta followed by a strong ERS activity in alpha, extended along of the epoch.

5.2.2 Power spectral results

In order to explore the differences of the ERD/ERS patterns among tasks in the two conditions, Figures 5.3 and 5.4 shows comparisons of the power changes of the TH task against the other imagery tasks (LH-RH) in both conditions using the same electrodes array from the same subject (*6*). Moreover, Figure 5.5 presents the power changes of the TH task in both conditions. The paired Wilcoxon signed-rank test was used to find out significant differences between tasks ($p<0.05$). They are shaded by gray blocks.

The differences presented by TH-LH and TH-RH are significantly more broad-banded at C3 than other channels in *Hands* condition (Figure 5.3). Meanwhile, Graz condition presents similar significant region sizes among the channels (Figure 5.4).

Figure 5.2 – Significant ERD/ERS patterns of the mental task at C3, Cz, C4 positions for Graz condition. An ERD activity is mainly found in the alpha band (8-12 Hz) at the three electrodes for the third hand (TH). The ERD/ERS patterns are widespread for left and right hands (LH, RH respectively) at the three electrodes. There is extensive activity in the resting state (RS).



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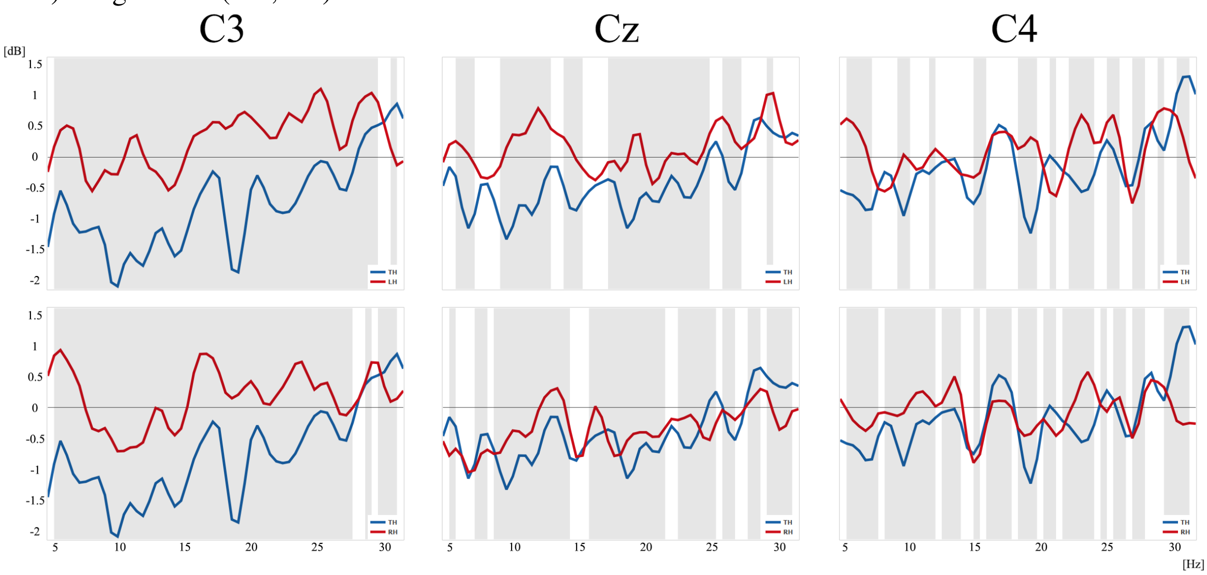
At C3, both cases (TH-RH, TH-LH) in Hands condition show significant differences in almost the whole frequency range. Conversely, in Graz condition, TH-RH shows more significant differences in alpha and low beta than TH-LH, but they share the significant region around 20Hz up to 25Hz. At Cz in Hands, the TH-LH comparison does not have a significant region in the alpha band, but it shares a low and middle beta with TH-RH, which has significant differences in some alpha and high beta sub-bands. For Graz in the same location, the TH-LH comparison indicates wide-spread sub-band regions for the beta, in alpha only a small region around 10hz is presented and, meantime, TH-RH shows a consistent region in alpha and low and high beta. Finally, at C4 in Hands, the TH-RH comparison shows more wide regions than TH-LH, especially in alpha and middle beta rhythms. The same behavior is presented in Graz condition, where TH-RH has more significant regions in alpha and low and middle beta than TH-LH, which does not have a significant difference in alpha, only in several sub-bands along beta, mainly upper than 15Hz.

Figure 5.3 – Comparison of the power changes of the mental tasks in the sensory-motor area (C3, Cz, C4) in Hands condition. Top: Third hand (TH, blue) - Left hand (LH, red). Bottom: Third hand (TH, blue) - Right hand (RH, red).



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In the comparison of the TH task between conditions (Figure 5.5), the ERS patterns are stronger in Hands than Graz, in line with the ERS/ERD maps (Figures 5.1 and 5.2). Such difference is more evident at C3 than the other channels. Likewise, C3 noticeably shows significant regions within both alpha and beta rhythms, whereas Cz is more often in middle and high beta, and C4 in alpha and middle beta.

5.3 Discussion

The presented patterns (figures 5.1 and 5.2) suggest a significant decreasing activity in the sensorimotor area caused by realistic training in comparison with the Graz. Besides, the ERD activity of the TH task is widespread, and its strength is keeping along of the epoch at the three sensorimotor channels (more at C3 than others) which could suggest that there is not a compulsory hemisphere governing the control and action of the imaginary arm. Besides, these facts motivate the author to adopt several time windows and frequency bands in order to obtain the most suitable combination for classification (see Chapter 4).

Nevertheless, the analysis of the power changes between tasks (Figures 5.3 and 5.4) show that there are more significant regions at C3 than the other electrode positions. The fact above could indicate that the user's handedness influences the region where TH task presents more activity. In the same way, the common ERD/ERS patterns are visible in both LH and RH tasks, although it is more evident in RH than LH. However, these patterns were missed in TH (only an increasing power activity was found in high frequencies: $> 25Hz$). It could suggest that the absence of symmetry of the third arm does not elicit a supplementary ERD activity for this task.

Finally, the unexpected activities presented in the resting state (RS) could be caused by the inertia of the motor/imagery movement. The paradigm to be adopted in the future should

Figure 5.4 – Comparison of the power changes of the mental tasks in the sensory-motor area (C3, Cz, C4) in Graz condition. Top: Third hand (TH, green) - Left hand (LH, orange). Bottom: Third hand (TH, green) - Right hand (RH, orange).

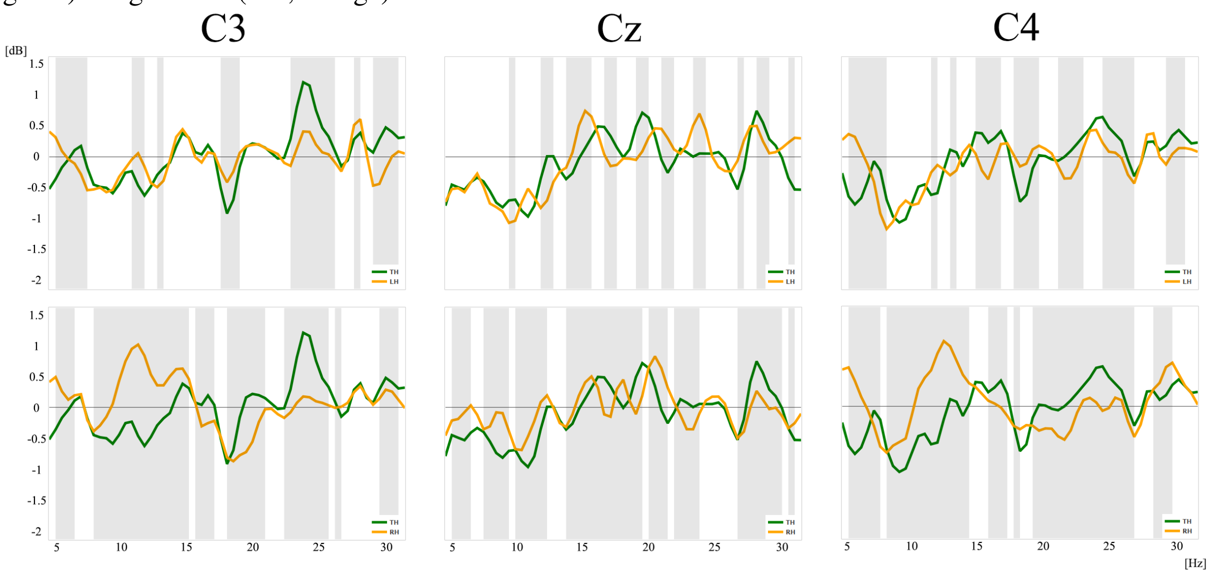

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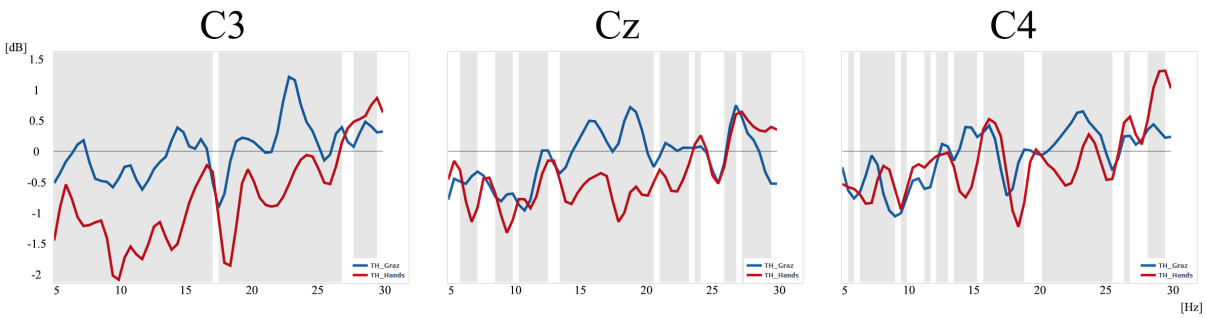
Figure 5.5 – Comparison of the power changes of the third arm task in the sensory-motor area (C3, Cz, C4) for both conditions. Blue: Third hand in Graz condition. Red: Third hand in Hands condition.



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include a blank space between the motor task and resting state so that the movements could be easily excluded.

6 CLASSIFICATION FRAMEWORK

6.1 Summary

The present chapter synthesis the classification results. Initially, all error rates obtained from each classifier are presented graphically. Consequently, the best combination of the time window, number of features and classifier is presented for each subject and condition. Likewise, the distribution of the number of features among the task is presented in order to find out the most used frequency bands. In overall, the error rates indicate that Hands condition significantly outperforms (u=0.32) the Graz (u=0.36) in the classification. Furthermore, the classification of TH-LH was better than the other two motor imagery condition (TH-RH, LH-RH) in both conditions (Graz = 0.34, Hands=0.29). It could suggest that the third virtual task is done with some handedness, since that it is better distinguished the non-dominant hand of the user.

6.2 Results

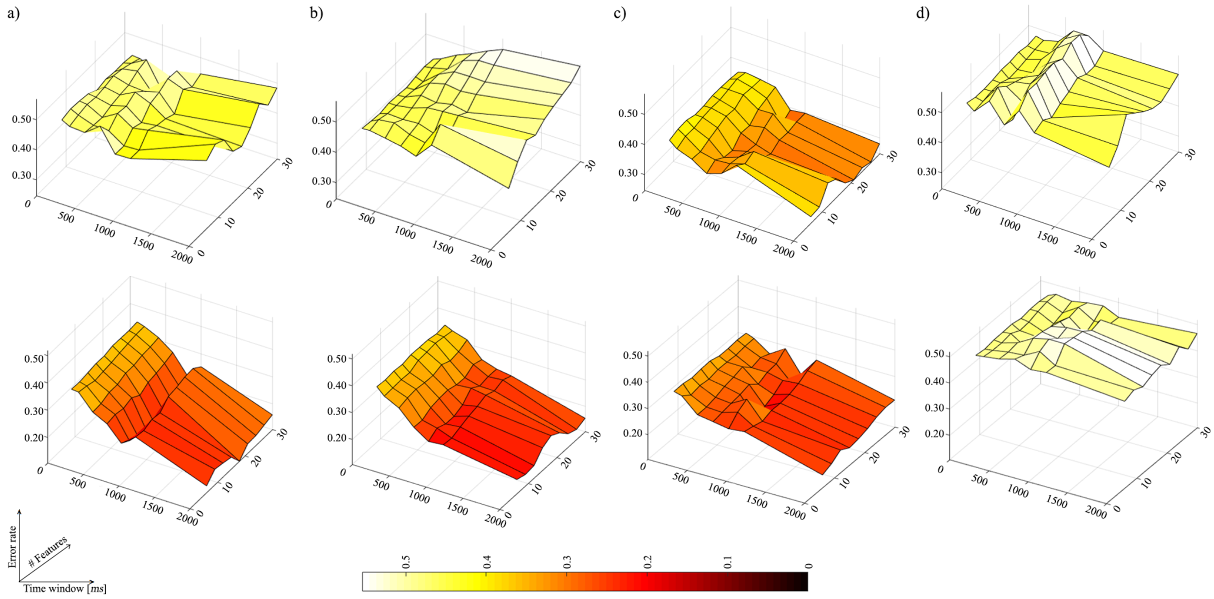
The Figures 6.1, 6.2 and 6.3 show error rates of the SVM, KNN and LDA classifiers respectively for each binary classification (Third hand (TH) - Left hand(LH), TH - Right Hand (RH), TH - Resting state (RS), and LH-RH). These rates are in function of the number of features and the size of the time windows. The surfaces are obtained for both Graz (top) and Hands (bottom) conditions.

Initially, the SVM surfaces of Graz condition (top Figure 6.1) shows that the third virtual arm is classified with better accuracies from resting state than the other two arms, exhibiting a decreasing behavior from a time window of 1000 ms and more prominent when the number of feature increases. The TH-LH and LH-RH present variable fluctuation along both time window and number of features, the last one with higher peaks. Meanwhile, TH-RH shows that error rates increase as a higher number of features. In the other hand, Hands condition surfaces (bottom Figure 6.1) show that error rates decrease as the time window increase in TH-LH, TH-RH, and TH-RS (with error rates lower thant 0.20), while LH-RH presents a flat-shape behavior. The number of features does not seem to affect error rates considerably (few fluctuations).

KNN surfaces of Graz condition (top Figure 6.2) presents that TH-RH has lower error rates than the other classifications. The time window influences the error rates, being notable from 1000ms, and the number of features remains unclear, fewer numbers reach low error rates for TH-RH and TH-RS (up to 20), but fluctuations are present in TH-LH and LH-RH. Meanwhile, the surfaces of Hands condition (bottom Figure 6.2) shows a consistent decrease activity in function of the time (1000 ms onwards), the fluctuation of the number of features is still presented, but in TH-RS error rates tend to be lower as the number of features increases.

Finally, LDA surfaces are quite similar to SVM surfaces in both conditions. In Graz (top 6.3), TH-RS has lower error rates than the other cases. Besides, the TH-RH and TH-RS show that error rates rise in function number of features, while a reduction is visible as the time window is longer. In the other side, the Hands surfaces (bottom 6.3) continues with the tendency presented by the two other classifiers, in other words, error rates decrease as the time window is

Figure 6.1 – Error rates over number of features and time window size for all users. Top: Graz condition. Bottom: Hands condition. The four binary classification are represented by a)TH-LH; b)TH-RH; c)TH-RS; and d)LH-RH.



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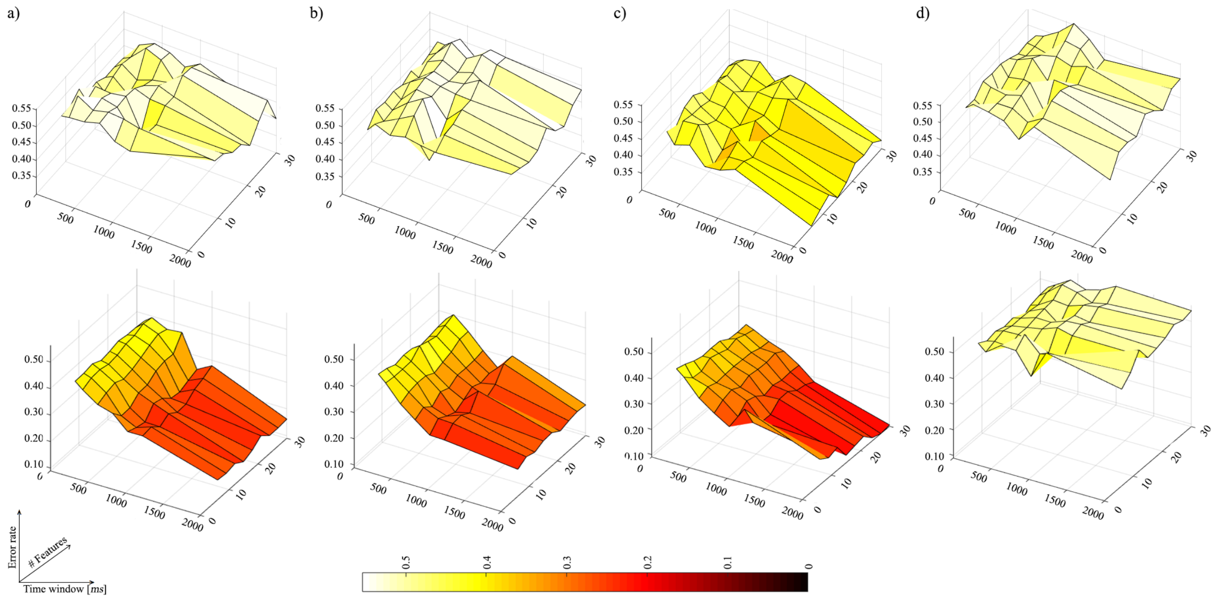
more prolonged, while the number of features shows a quasi-flat behavior, with weak influence in comparison with the time window (minor increases as the number of feature rises).

It can be seen clearly that Hands condition reached lower error rates than Graz in the three classifiers. Likewise, error rates are lower in the classification that includes the third arm than the left and right classification; in effect, RH-LH classification in some cases reached error rates close to 0.5. Finally, the tendency in both conditions is that error rates decrease as the time window increases (1000ms onwards), but in the number of features is unclear, with fluctuations among tasks and conditions.

Following the error mean values of each window\feature, a greedy algorithm is run in order to find the optimal global choice. Thus, for each subject, it is possible to obtain the best combination of the three conditions (i.e., number of features (NF), size of the window (SW) and classifier (C)) and, therefore, to pick up the best miss-classification rate (error). Table 6.1 shows these values in Graz (G) and Hands (H) conditions among the subjects.

The mean error obtained over all participants (n=10) in Hands condition was approx 32% (i.e. TH-LH: 0.29 ± 0.03, TH-RH: 0.29 ± 0.03, TH-RS: 0.29 ± 0.03, and LH-RH: 0.39 ± 0.01) and around 36% in Graz condition (i.e. TH-LH: 0.34 ± 0.02, TH-RH: 0.38 ± 0.02, TH-RS: 0.29 ± 0.02, and LH-RH: 0.42 ± 0.01). Pairwise comparison using paired Wilcoxon signed rank test with Bonferroni correction reveals a significant (V = 0, p-value = 0.048) between conditions. Likewise, Dunn's Kruskal-Wallis Multiple Comparisons with Bonferroni correction show significant difference among groups, exactly in both TH-LH (z=-2.49, p-value=0.03) and TH-RS (z=-3.92, p-value=0.0003) against LH-RH for Graz, and in Hands only for TH-RS (z=-2.44, p-value=0.04).

Figure 6.2 – Error rates over number of features and time window size for all users. Top: Graz condition. Bottom: Hands condition. The four binary classification are represented by a)TH-LH; b)TH-RH; c)TH-RS; and d)LH-RH.



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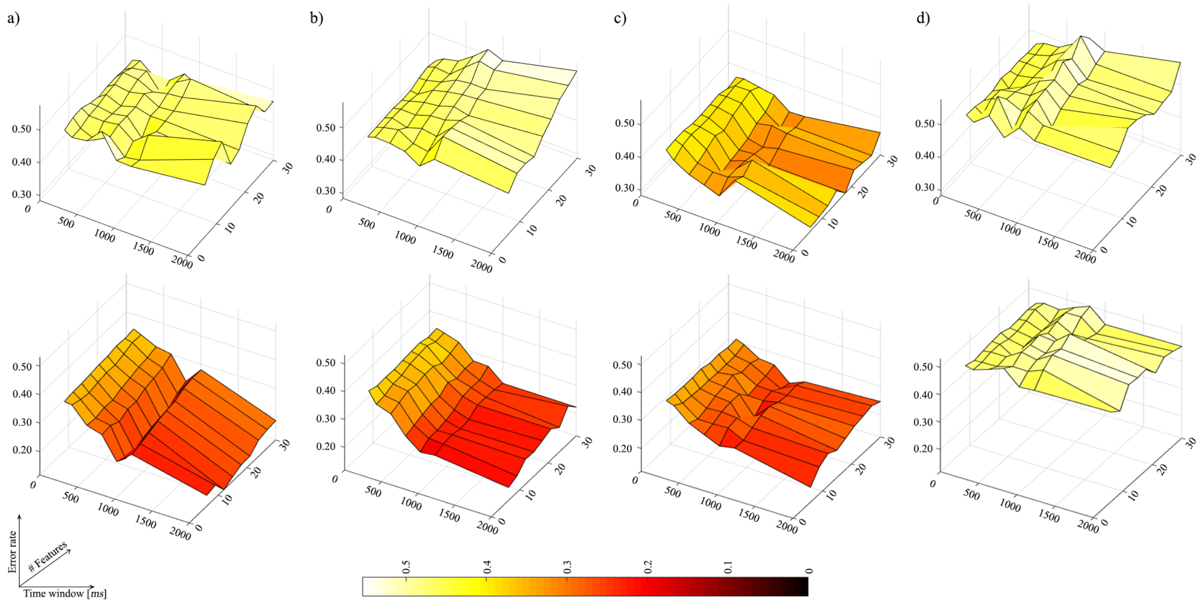
Furthermore, Table 6.1 shows that time windows of 800ms up to 2000ms (maximum time) were often used in classification that includes the third arm (TH-RH,TH-LH and TH-RS). In the classifiers, KNN was the most used among the participants and conditions. Moreover, for the number of feature, there are several variations across the subjects and conditions. Only in TH-RS, the number of features was widespread. Otherwise, the distribution was concentrated from six up to 21. Precisely, Figure 6.4 shows the histogram of selection of each frequency component over all subjects for the four binary classifications. In the figure can be seen that frequency components in the alpha and beta3 (24-30Hz) were selected for most of the participants, in effect, the clear peaks are inside these ranges. Meanwhile, the whole beta band (beta 4, 13-30Hz) was few used, showing how the beta sub-bands can be more useful than the whole band itself.

6.3 Discussion

The high error rates reached by the left-right hand classification (LH/RH) in both conditions (Hands: 0.39 ± 0.01 Graz: 0.42 ± 0.01) could suggest that the inclusion of the third arm would cause the reduction of its accuracy because the users could interpret either left and right hand as the third arm. Whereas, the third arm is distinguished from the left hand than the right with better accuracies. It could support the fact that the TH task follows the activity based on the handedness. Unfortunately, all of our subjects were right-handed, so we can not evaluate the handedness thoroughly in this experiment.

Figure 6.3 – Error rates over number of features and time window size for all users. Top: Graz condition. Bottom: Hands condition. The four binary classification are represented by a)TH-LH; b)TH-RH; c)TH-RS; and d)LH-RH.



Source: the author

Evidently, and in line with the previous works [Skola and Liarokapis 2018, Braun et al. 2016], both the classification rates and the modulation of ERS signals were enhanced by the realistic training, evidencing its importance inside the BCI loop. Also, our work goes further than the one done by Skola and Liarnokapis [Skola and Liarokapis 2018] because they compared the embodiment VR scenario against the monitor-based Graz, creating a bias in the users who started with the VR. Here, the comparison was made with both Graz and Hands experimental conditions made in VR.

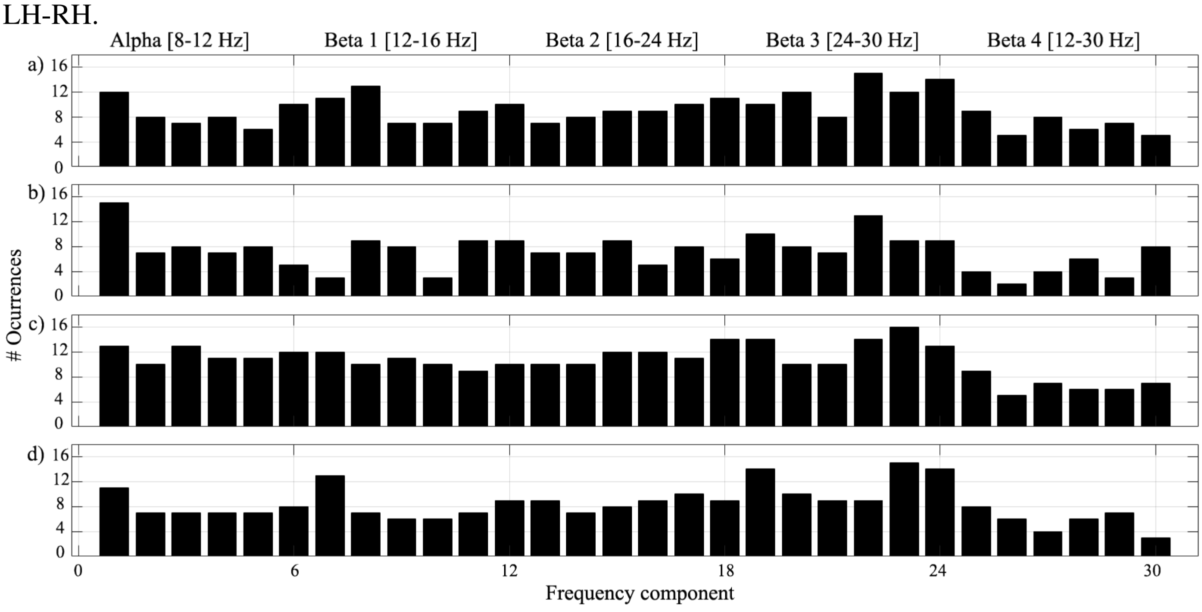
The decision of exploring the influence of both the time window and the number of features in the classification, including three different types of classifiers, sheds light upon the high variations among subjects and tasks, in effect, it demonstrates that the design of an MI-BCI system is a subject-sensitive case. Furthermore, the use of multiple learning algorithms inside of the BCI loop could help to obtain better performances, where a classifier could be used instead of others when its accuracy is higher.

Table 6.1 – The best combinations of number of features, time window and classifier and the error rates reached with them across the subjects for both conditions. The asterisks indicate the subjects that began the experiment with the Hands condition.

Subject	**Condition**	**TH-RH**				**TH-LH**				**TH-RS**				**LH-RH**			
		NF	SW	C	Error	NF	SW	C	Error	NF	SW	C	Error	NF	SW	C	Error
1*	G	6	2000	KNN	**0.18**	6	2000	KNN	**0.18**	6	800	LDA	**0.24**	9	2000	LDA	0.42
	H	9	2000	LDA	**0.17**	12	2000	KNN	0.28	15	1000	SVM	0.27	12	2000	SVM	0.41
2	G	6	800	SVM	0.26	24	100	KNN	0.40	9	2000	SVM	**0.16**	6	2000	KNN	0.30
	H	6	2000	KNN	**0.19**	6	2000	LDA	**0.13**	24	2000	SVM	**0.24**	21	800	KNN	0.39
3	G	6	800	LDA	0.42	6	800	KNN	0.41	12	2000	KNN	0.35	21	600	KNN	0.45
	H	12	1000	SVM	0.40	9	2000	KNN	0.34	12	2000	KNN	0.27	6	100	KNN	0.48
4*	G	30	100	KNN	0.42	6	800	LDA	0.41	24	1000	KNN	0.37	6	100	SVM	0.46
	H	15	100	KNN	0.47	6	400	LDA	0.45	18	600	KNN	0.37	6	1000	SVM	0.36
5	G	30	800	SVM	0.31	6	100	LDA	0.46	12	600	KNN	0.28	15	100	KNN	0.45
	H	12	2000	KNN	0.34	24	800	SVM	0.41	15	400	KNN	0.42	12	2000	KNN	0.38
6*	G	21	2000	KNN	0.40	6	100	LDA	0.42	18	2000	SVM	0.26	6	800	KNN	0.45
	H	18	2000	SVM	**0.10**	6	2000	SVM	**0.16**	30	2000	KNN	**0.09**	21	400	SVM	0.42
7	G	15	2000	SVM	0.38	18	800	SVM	0.38	21	400	SVM	0.37	21	2000	KNN	0.41
	H	21	200	LDA	0.28	30	1000	KNN	0.38	9	1000	SVM	0.34	6	800	SVM	0.44
8*	G	6	800	LDA	0.36	9	800	SVM	0.40	18	2000	SVM	0.31	6	200	SVM	0.46
	H	9	800	SVM	0.39	12	800	LDA	0.41	6	800	LDA	0.35	21	800	LDA	0.37
9	G	12	800	KNN	0.38	6	100	SVM	0.48	27	2000	KNN	0.34	15	600	LDA	0.40
	H	21	1000	KNN	0.31	9	1000	SVM	**0.22**	27	800	KNN	0.37	9	800	LDA	0.37
10*	G	12	800	KNN	0.32	9	800	LDA	0.34	6	2000	KNN	**0.22**	6	100	SVM	0.46
	H	6	800	SVM	**0.25**	6	2000	KNN	**0.21**	9	2000	LDA	**0.22**	6	2000	SVM	0.36

Source: the author

Figure 6.4 – Relevant frequency components over all subjects. a) TH-LH; b) TH-RH; c) TH-RS; d) LH-RH.



Source: the author

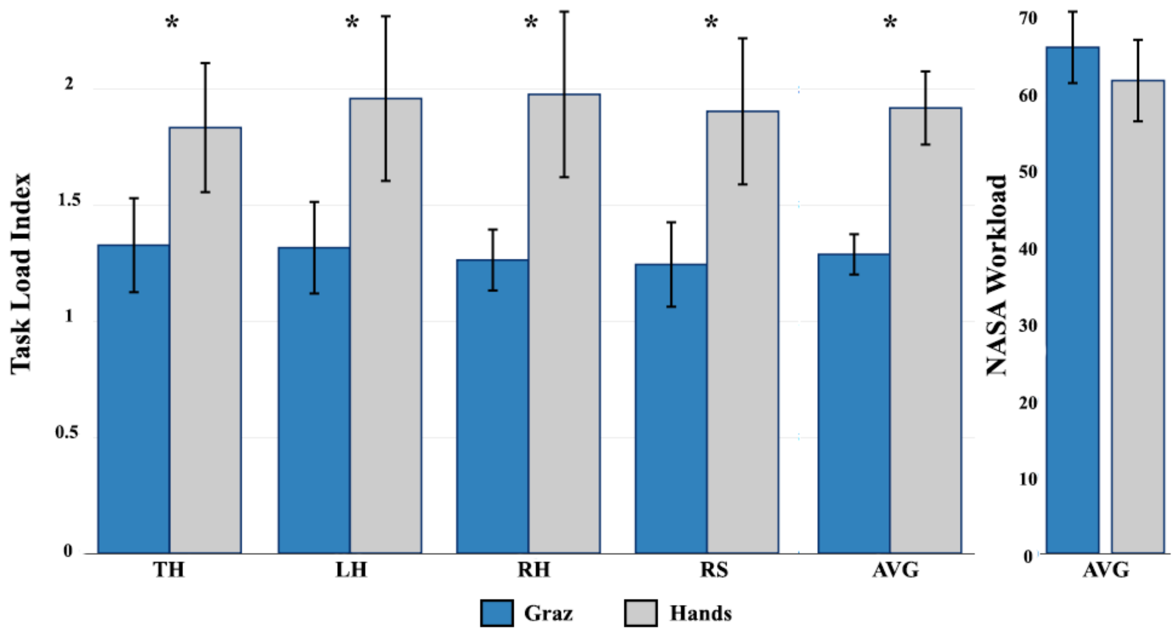
7 COGNITIVE LOAD AND MIQ-3 QUESTIONNAIRE

7.1 Summary

The previous chapter successfully demonstrated that realistic training improves the accuracy in the classification as well as elicits more ERS/ERD patterns than the traditional Graz paradigm. This chapter focuses on studying the influence that Hands condition has in the users in terms of the cognitive load. Effectively, the Task Load Index assessment reveals that this condition has a higher cognitive load than the Graz. Conversely, the users perceived the opposite thing in the subjective assessment. Finally, the imagery questionnaire shows that the External Visual Imagery was more natural to the users, but it does not have any relationship with the classification performance.

7.2 Results

Figure 7.1 – Task Load Index and NASA Workload for the two conditions. * Significant differences



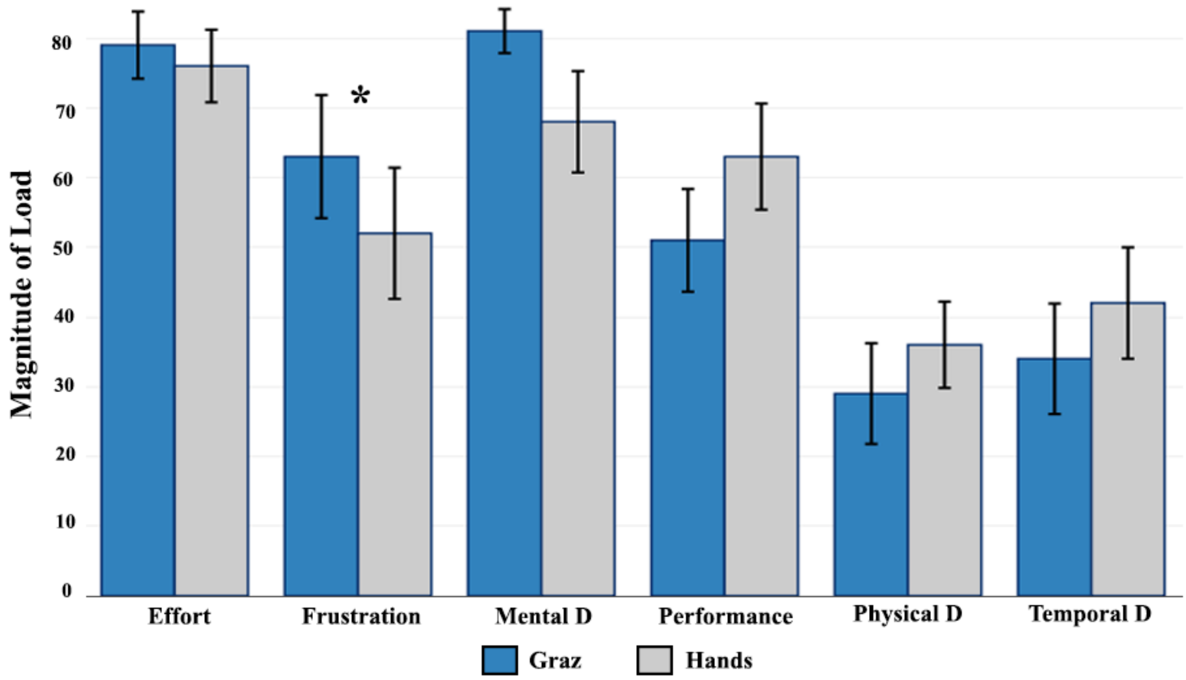
Source: the author

Figure 7.1 shows the cognitive load of both objective (Task Load Index) and subjective (NASA-TLX). The cognitive load assessed by the Task Load Index reflects the fact of that Hands condition has a significantly higher cognitive load than the Graz (pairwise paired Wilcox with Bonferroni: V = 656, p-value = 0.00063). There is no significant difference among task. Meanwhile, the subjective assessment of the cognitive load reflects the opposite; NASA Workload points to a higher cognitive load in Graz condition than in Hands although significance could not be found (paired t-test: t=0.829, p-value=0.428).

Moreover, Figure 7.2 shows that Hand condition presents a non-significant higher Load Magnitude than Graz in factors such as Performance, Physical and Temporal demand. Nevertheless, a pairwise paired Wilcoxon reflects that there is a significant difference between conditions in the Frustration factor (V=210, p-value= 0.049), indicating a higher sense of frustration in Graz than Hands condition.

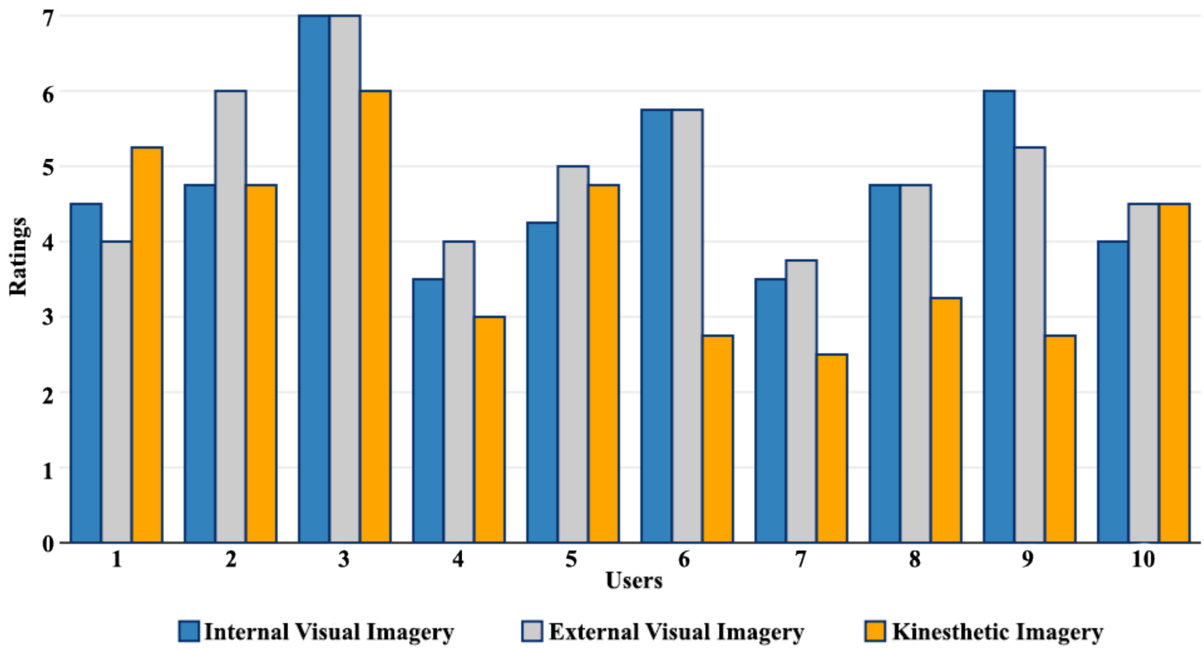
Finally, Figure 7.3 summarizes the user's answers of the MIQ-3 questionnaire, the ratings represent how easy (7) or hard (1) was to perform the imagery task (see Appendix A). The mean values show that External Visual Imagery (5 ± 1.02) was easier for the users than Internal Visual Imagery (4.8 ± 1.13) and Kinesthetic Imagery (3.95 ± 1.24). Moreover, Spearman's rank correlation is used in order to find out any relationship between the classification error and both the questionnaires (NASA-TLX and MIQ-3) and the Task Load Index. There are no any significant correlations in both MIQ-3 and Task Load Index with the performance of the users. Meanwhile, in the NASA-TLX, there is a significant correlation (rho=-0.366, p-value=0.019) in Mental demand factor for the Hand condition. Inside this condition, only the TH-LH classification has a significant correlation with this factor (rho=-0.693, p-value=0.0261).

Figure 7.2 – NASA factors for the two conditions. *Significant difference.



Source: the author

Figure 7.3 – MIQ-3 results. Ratings range from 1 (very hard) to 7 (very easy).



Source: the author

7.3 Discussion

The aim of studying the cognitive load in both subjective and objective ways is for a deeper understanding of the additional load that realistic and visual feedback could cause. In effect, the outcome of the objective assessment (Task Load Index) goes against to the results of the subjective one (NASA-TLX). EEG data reveals that the cognitive load is higher (significantly) in the realistic condition (Hands) than the standard one (Graz) but the opposite is presented in the NASA-TLX (without significance). Moreover, some user's comments at the end of the experiment, such as "I found harder the arrows than the arms" or "I feel Temporal demand a bit easier in Hands than Graz because it is easier to visualize" and the opposite "... The arrow session was a less hard than the virtual hands because with the arms I constantly tried to follow the hand movements which did not happen with the arrows" could evidence the disjunctive sensation of the users evidenced by the NASA and Task Load Index. Interestingly, a user did the next comment "The fact that I had the possibility of performing real hand movement helped me to release the stress created by the imagery tasks" This comment supports the intention of keeping the real movements but further studies and comparisons are necessary before drawing conclusions.

Despite that the Hands condition was kept as simple as possible, it could not be possible to maintain a low cognitive load like in Graz, in effect, the processing of visual animation is higher than arrows and fixation cross, showing how the visual processing plays a vital role in the task load.

8 CONCLUSION AND FUTURE WORK

8.1 Contributions

This thesis investigated the possibility of using an imaginary third arm inside a MI-BCI system as well as the differences of the EEG patterns and classification rates of using a realistic visual training in comparison of the traditional visualization.

Initially, the common EEG patterns of motor imagery activity (ERD/ERS) are found when the subjects were asked to imagine a hand movement of a third arm emerging from the chest. These findings can suggest that the illusion of having a third arm could go further than a Rubber Hand illusion since that, in this case, a limb is attached and included rather than replaced as RHI does. Furthermore, this thesis demonstrates that such imaginary third hand can be successfully classified from other imaginary tasks (left and right hand), and resting state. The results of table 6.1 suggest that the classification distinguishes this third arm from the left hand and the resting state conditions with higher accuracy rates than it does from the right hand. This seems to be related to handedness.

Additionally, and in line with the previous findings done by Skola and Liarnokapis [Skola and Liarokapis 2018], the embodiment training improves the classification performance as well as elicits stronger and consistent ERS/ERD patterns than the traditional Graz paradigm. However, such comparison, unlike of Skola and Liarnokapis, is done in VR, i.e., both conditions were made in a VR scenario, eliminating the bias that there exist when the comparison is made with Graz in a monitor-based presentation.

Finally, the thesis shows the influence that realistic training has in the user, demonstrating thus that the cognitive load is higher in this scenario. However, the benefits presented by this feedback are reflected in the enhanced of the ERS signals that consequently produce an improvement of the classification.

8.2 Limitations

Unfortunately, this work lacks in studies about ownership of the third-arm in both subjectively, with questions about the sense of agency and sense of ownership, and objectively, using galvanic skin response (GSR), following the work of Bashford and Mehring [Bashford and Mehring 2016]. These data could give some insights regarding the use of supernumerary BCI and how it could be used in real applications, coming from the answers of the users.

8.3 Future Works

It would be necessary to experiment with left-handed people, in order to study the handiness of the third arm. Moreover, it is compulsory the online MI-BCI implementation of the proposed framework and paradigm, including the online recognition of the third virtual arm from the other imaginary tasks.s

Supernumerary MI-BCI systems are prominent and possible uses should be explored, especially for VR applications, where customized avatars could be controlled using imaginary non-body signals.

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APPENDIX A — MIQ-3 QUESTIONNAIRE

Movement Imagery Questionnaire - 3 (MIQ - 3)

Instruções:

Este questionário diz respeito a duas formas de desempenho mental de movimentos, as quais são usadas por algumas pessoas mais que outras, e são mais indicadas para alguns tipos de movimentos do que outros.

Primeiro, tenta-se formar uma imagem visual ou a figura do movimento na mente. Em seguida, tenta-se sentir a execução da ação sem realmente realizar o movimento.
Será solicitada a realização de ambas as tarefas mentais em movimentos variados neste questionário, e em seguida qu que se classifique conforme a facilidade/dificuldade encontrada na realização das tarefas.

As classificações não estão designadas para avaliar a facilidade ou dificuldade da forma como realiza as tarefas mentais. Elas são tentativas para descobrir a capacidade individual para a realização das tarefas para movimentos diferentes. Não existem classificações certas ou erradas ou classificações melhores que outras.

Cada uma das seguintes afirmações descreve uma ação particular ou movimento. Leia cada afirmação cuidadosamente e em seguida realize o movimento como é descrito. Realize o movimento uma única vez. Retorne para a posição inicial como se fosse realizar a ação, uma segunda vez. Depois, dependendo do que for pedido para realizar, ou (1) formar de forma clara e vivida, quanto possível, a imagem visual do movimento realizada apenas a partir de uma perspectiva interna (i.e. a partir da perspectiva da 1ª pessoa, como se estivesses realmente dentro de si realizando e vendo a ação através dos seus olhos), (2) formar de forma clara e vivida, quanto possível, a imagem visual do movimento realizada apenas a partir de uma perspectiva externa (i.e. a partir da perspectiva da 3ª pessoa, como se estivesse vendo num filme), ou (3) tentar sentir como se realizasse o movimento acabado de executar sem realmente realizá-lo.

Após completar a tarefa mental requerida, classifique a facilidade/dificuldade de realizar a tarefa. Classifique a partir da escala fornecida e tente ser o mais preciso possível. Use o tempo que for necessário para decidir a classificação mais adequada para cada movimento. Pode escolher a mesma classificação para qualquer número de movimentos “vistos” ou “sentidos” e não é necessário utilizar toda a amplitude da escala.

* Required

1. **ID** *

____

1) Levantar o joelho

Posição Inicial:

Coloque-se com os pés e pernas juntos e os braços ao longo do corpo.

Ação:

Levante o joelho direito o mais alto possível de forma a permanecer de pé sobre a sua perna esquerda, com a perna direita fletida (dobrada) no joelho. Agora, baixe a sua perna direita para voltar a ficar de pé sobre os dois pés. A ação é executada lentamente.

Tarefa Mental:

Assuma a posição inicial. Tente sentir-se realizando o movimento já observado mas sem o executar. Agora classifique a facilidade/dificuldade encontrada na realização da tarefa mental.

2. **Classificação** *

Mark only one oval.

- Muito difícil de sentir
- Difícil de sentir
- Um pouco difícil de sentir
- Neutro (nem fácil nem difícil)
- Um pouco fácil de sentir
- Fácil de sentir
- Muito fácil de sentir

2) Salto

Posição Inicial:

Coloque-se com os pés e pernas juntas e os braços ao longo do corpo.

Ação:

Curve-se para baixo e em seguida salte em linha reta para cima, o mais alto possível, com ambos os braços estendidos acima da cabeça. Pouse com os pés afastados e baixe os braços.

Tarefa Mental:

Assuma a posição inicial. Tente ver-se realizando o movimento já observado a partir da perspectiva interna. Agora classifique a facilidade/dificuldade encontrada na realização da tarefa mental.

3. **Classificação** *

Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

3)Movimento do braço

Posição Inicial:

Estenda o braço da sua mão não-dominante lateralmente de maneira que ele fique paralelo ao solo com a palma da mão para baixo

Ação:

Desloque o seu braço para frente do corpo (ainda paralelo ao solo). Mantenha o braço estendido durante o movimento, executando-o lentamente.

Tarefa Mental:

Assuma a posição inicial. Tente ver-se realizando o movimento já observado a partir da perspectiva externa. Agora classifique a facilidade/dificuldade encontrada na realização da tarefa mental.

4. **Classificação** *

Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

4) Dobrar a cintura

Posição Inicial:

Coloque-se com os pés ligeiramente afastados e os braços completamente estendidos acima da cabeça.

Ação:

Lentamente, dobre o seu corpo para frente pela cintura tentando tocar nos dedos dos pés com a ponta dos dedos das mãos (ou, se possível, tocar no solo com a ponta dos dedos ou com as mãos). Agora, volte à posição inicial permanecendo ereto com os braços estendidos sobre a cabeça.

Tarefa Mental:

Assuma a posição inicial. Tente sentir-se realizando o movimento já observado sem o executar. Agora, classifique a facilidade/dificuldade encontrada na realização da tarefa mental.

5. **Classificação** *
Mark only one oval.

- Muito difícil de sentir
- Difícil de sentir
- Um pouco difícil de sentir
- Neutro (nem fácil nem difícil)
- Um pouco fácil de sentir
- Fácil de sentir
- Muito fácil de sentir

5) Levantar o joelho

Posição Inicial:

Coloque-se com os pés e pernas juntos e os braços ao longo do corpo.

Ação:

Levanta o joelho direito o mais alto possível de forma a permaneceres de pé sob a tua perna esquerda com a perna direita fletida (dobrada) no joelho. Agora baixa a tua perna a tua perna direita para voltares a estar de pé sob os dois pés. A ação é executada lentamente.

Tarefa Mental:

Assume a posição de inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva interna. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

6. **Classificação** *
Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

6) Salto

Posição Inicial:

Coloca-te com os pés e pernas juntas e os braços ao longo do corpo.

Ação:

Curva-te para baixo e de seguida salta em linha recta para cima, o mais alto possível, com ambos os braços estendidos acima da cabeça. Aterra com os pés afastados e baixa os braços.

Tarefa Mental:

Assume a posição inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva externa. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

7. **Classificação** *

Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

7)Movimento do braço

Posição Inicial:

Estende o braço da tua mão não-dominante para o lado do corpo de maneira que ele fique paralelo ao solo com a palma da mão para baixo

Ação:

Desloca o teu braço para frente do corpo (ainda paralelo ao solo). Mantem o braço estendido durante o movimento, executando-o lentamente.

Tarefa Mental:

Assume a posição de inicial. Tenta sentir-te a realizar o movimento já observado sem o executar. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

8. **Classificação** *
Mark only one oval.

- Muito difícil de sentir
- Difícil de sentir
- Um pouco difícil de sentir
- Neutro (nem fácil nem difícil)
- Um pouco fácil de sentir
- Fácil de sentir
- Muito fácil de sentir

8) Dobrar a cintura

Posição Inicial:

Coloca-te com os pés ligeiramente afastados e os braços completamente estendidos acima da cabeça.

Ação:

Lentamente dobra o teu corpo para frente pela cintura tentando tocar nos dedos dos pés com a ponta dos dedos das mãos (ou, se possível, tocar no solo com a ponta dos dedos ou com as mãos). Agora volta à posição inicial permanecendo direito com os braços estendidos sobre a cabeça.

Tarefa Mental:

Assume a posição de inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva interna. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

9. **Classificação** *
Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

9) Levantar o joelho

Posição Inicial:

Coloca-te com os pés e pernas juntas e os braços ao longo do corpo.

Ação:

Levanta o joelho direito o mais alto possível de forma a permaneceres de pé sob a tua perna esquerda com a perna direita fletida (dobrada) no joelho. Agora baixa a tua perna a tua perna direita para voltares a estar de pé sob os dois pés. A ação é executada lentamente.

Tarefa Mental:

Assume a posição inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva externa. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa

10. **Classificação** *

Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

10)Salto

Posição Inicial:

Coloca-te com os pés e pernas juntas e os braços ao longo do corpo.

Ação:

Curva-te para baixo e de seguida salta em linha reta para cima, o mais alto possível, com ambos os braços estendidos acima da cabeça. Aterra com os pés afastados e baixa os braços.

Tarefa Mental:

Assume a posição de inicial. Tenta sentir-te a realizar o movimento já observado sem o executar. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

11. **Classificação** *
Mark only one oval.

- Muito difícil de sentir
- Difícil de sentir
- Um pouco difícil de sentir
- Neutro (nem fácil nem difícil)
- Um pouco fácil de sentir
- Fácil de sentir
- Muito fácil de sentir

11) Movimento do braço

Posição Inicial:

Estende o braço da tua mão não-dominante para o lado do corpo de maneira que ele fique paralelo ao solo com a palma da mão para baixo

Ação:

Desloca o teu braço para frente do corpo (ainda paralelo ao solo). Mantem o braço estendido durante o movimento, executando-o lentamente.

Tarefa Mental:

Assume a posição de inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva interna. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa mental.

12. **Classificação** *
Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

12) Dobrar a cintura

Posição Inicial:

Coloca-te com os pés ligeiramente afastados e os braços completamente estendidos acima da cabeça.

Ação:

Lentamente dobra o teu corpo para frente pela cintura tentando tocar nos dedos dos pés com a ponta dos dedos das mãos (ou, se possível, tocar no solo com a ponta dos dedos ou com as mãos). Agora volta à posição inicial permanecendo direito com os braços estendidos sobre a cabeça.

Tarefa Mental:

Assume a posição inicial. Tenta ver-te a realizar o movimento já observado a partir da perspetiva externa. Agora classifica a facilidade/dificuldade encontrada na realização da tarefa.

13. **Classificação** *

Mark only one oval.

- Muito difícil de ver
- Difícil de ver
- Um pouco difícil de ver
- Neutro (nem fácil nem difícil)
- Um pouco fácil de ver
- Fácil de ver
- Muito fácil de ver

Obrigado!

Podemos agora começar com o set-up do experimento.

APPENDIX B — DEMOGRAPHIC AND EDINBURGH HANDEDNESS QUESTIONNAIRES. CONSENTING TERM AND EXPERIMENT INSTRUCTIONS

Formulário de Participação

Deve ser preenchido antes de agendar o horário de participação no experimento.

* Required

1. **Email address** *

2. **Nome** *

Termo de Consentimento

Você está convidado a participar de um experimento cujo objetivo é pesquisar e desenvolver Interfaces Homem-Computador, através de métodos de Eletroencefalografia (EEG) e Realidade Virtual (VR).

As aplicações dos testes serão no Instituto de Informática da UFRGS, por aproximadamente 60 minutos e constam de três sessões.

Sua participação na pesquisa é totalmente voluntária, ou seja, não é obrigatória. Não está previsto nenhum tipo de pagamento pela sua participação na pesquisa e você não terá nenhum custo com respeito aos procedimentos envolvidos.

Caso você decida não participar, ou ainda, desistir de participar e retirar seu consentimento, não haverá nenhum prejuízo ao atendimento que você recebe ou possa vir a receber na instituição.

O sigilo da identidade do entrevistado será mantido, uma vez que será realizada a substituição dos nomes e sobrenomes por códigos numéricos. Os resultados serão apresentados de forma conjunta, sem a identificação dos participantes, ou seja, o seu nome não aparecerá na publicação dos resultados.

Não são conhecidos riscos pela participação na pesquisa pelos procedimentos envolvidos. Você apenas ficará com gel residual no couro cabeludo em função do uso da touca de EEG. Caso ocorra alguma intercorrência ou dano, resultante de sua participação na pesquisa, você receberá todo o atendimento necessário, sem nenhum custo pessoal.

A avaliação consiste nas seguintes tarefas:

Preenchimento de formulários demográficos e referentes à sua experiência no uso de tecnologias EEG e VR e questionário sobre a imaginação motriz.

Será colocada uma “touca” com eletrodos para mensuração da atividade cerebral (EEG) e um Head Mounted Display (HMD) para a simulação do ambiente imersivo.

Após a instalação destes equipamentos, você terá que fazer os testes explicados detalhadamente na folha anexa, entre testes terá um espaço de relaxamento.

Sua participação na pesquisa não trará benefícios diretos, porém contribuirá para o aumento do conhecimento sobre o assunto estudado e, se aplicável, poderá beneficiar ciência e muitas pessoas no futuro.

Salienta-se que, ao longo da pesquisa, os pesquisadores estarão à disposição para responder a quaisquer dúvidas relacionadas a tal. Abaixo constará o nome e telefone do pesquisador para eventual contato.

3. **Caso você esteja de acordo com este termo, marque a opção abaixo.** *
Check all that apply.

   - [ ] Aceito participar deste experimento. Declaro que fui devidamente informado sobre os objetivos da pesquisa, os procedimentos envolvidos nos testes aos quais vou me submeter e os possíveis riscos decorrentes de minha participação. Foi-me garantido o sigilo de minhas informações e o direito de retirar minha participação a qualquer momento.

Perfil do Participante

4. **Qual sua idade?** *

5. **Qual seu sexo?** *
Mark only one oval.
   - ( ) Feminino
   - ( ) Masculino

6. **Qual seu nível de formação?** *
Mark only one oval.
   - ( ) Ensino médio
   - ( ) Técnico
   - ( ) Graduado
   - ( ) Especialista
   - ( ) Mestrado
   - ( ) Doutorado
   - ( ) Pós doutorado

7. **Você tem alguma restrição em movimentar sua cabeça?** *

8. **Você tem problemas de visão?** *
Mark only one oval.
   - ( ) Sim
   - ( ) Não
   - ( ) Não sei

9. **Quais problemas de visão você possui? (se sim na pergunta acima)**
Check all that apply.

- [ ] Miopia
- [ ] Astigmatismo
- [ ] Hipermetropia
- [ ] Daltonismo
- [ ] Outro

10. **Você já usou Oculus Rift ou outro aparelho similar?** *
Mark only one oval.

- ( ) Não. Nunca usei aparelho similar.
- ( ) Sim. Já usei o Oculus Rift antes.
- ( ) Other: ____________________

11. **Marque a opção que melhor descreve qual mão você usa para a atividade em questão** *
Mark only one oval per row.

	Sempre Esquerda	Geralmente Esquerda	Sem Preferência	Geralmente Direita	Sempre Direita
Escrevendo	( )	( )	( )	( )	( )
Lançando um objeto	( )	( )	( )	( )	( )
Usando uma tesoura	( )	( )	( )	( )	( )
Escova de dentes	( )	( )	( )	( )	( )
Usando uma faca (sem garfo)	( )	( )	( )	( )	( )
Usando uma colher	( )	( )	( )	( )	( )
Acendendo um fósforo	( )	( )	( )	( )	( )

Instruções

Você vai estar sentado, da forma mais confortável e relaxada possível e procurando evitar o máximo possível qualquer outro movimento além do indicado para fazer. O experimento possui 6 etapas (Aplicação do questionário de caracterização, treinamento, calibração, dois testes e aplicação do questionário final):

-Aplicação do questionário de caracterização: Ao início do experimento, você será convidado a responder algumas perguntas demográficas (idade, sexo, educação) e um questionário de imaginação motriz.

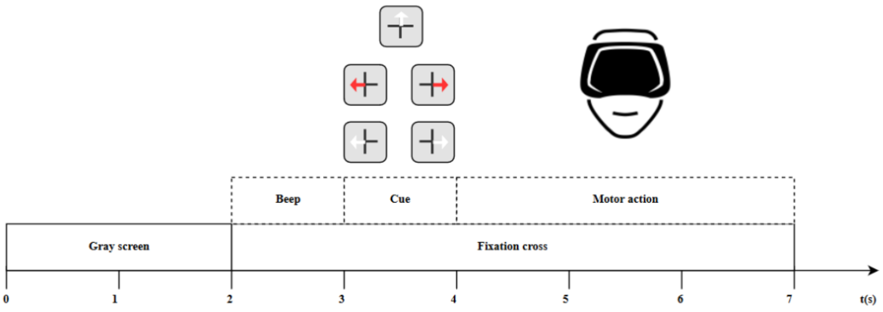
-Treinamento: Vai ser apresentada a cena do teste em realidade virtual para que você se habitue com o paradigma e os estímulos a serem apresentados. Instruções vão ser subministradas ao longo dessa etapa até você aprender o processo todo.

-Calibração: Uma touca branca com eletrodos (8) será colocada em sua cabeça, a mesma irá medir as ondas cerebrais, ela poderá ser um pouco desconfortável. Posteriormente, dois eletrodos a mais serão colocados detrás da sua orelha (mastoide).

-Experimento: Dois testes vão ser rodados (com um descanso de dois min no meio). Cada teste está composto de 100 triais com uma duração de sete segundos cada um (duração total 12min). Os triais dividem-se em quatro partes (ver figura 1):

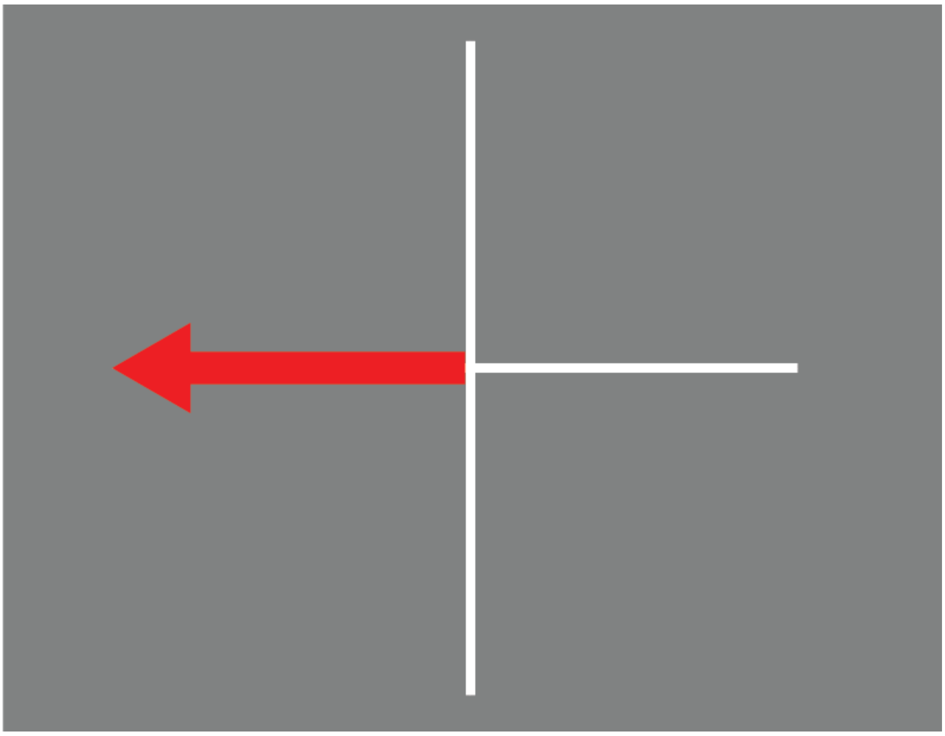
-Tela cinza: onde você deve ficar relaxado (2 segs).
-Sino: som indicando prestar atenção para a instrução a ser apresentada (1 seg).
-Seta: Aparece uma seta indicando a tarefa a ser executada (1 seg).
-Cruz: Ponto de fixação onde você deve executar a tarefa (3 segs).

Figura 1



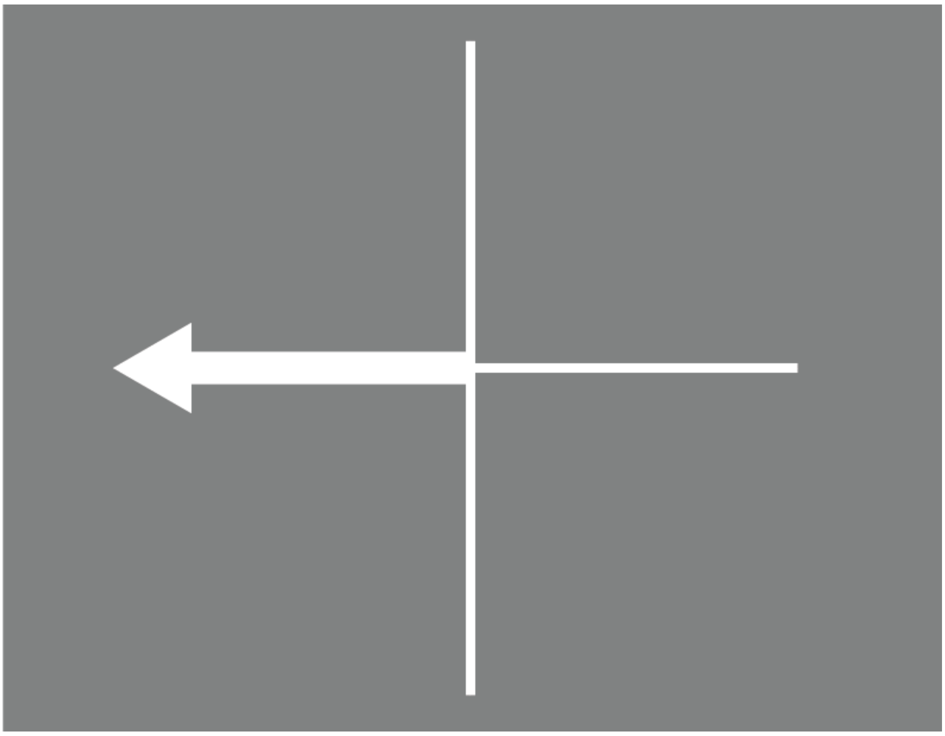
A direção (para cima, esquerda o direita) e a cor (branco e vermelho) das setas representam a tarefa a ser executada da seguinte forma:

Execução movimento mão esquerda.

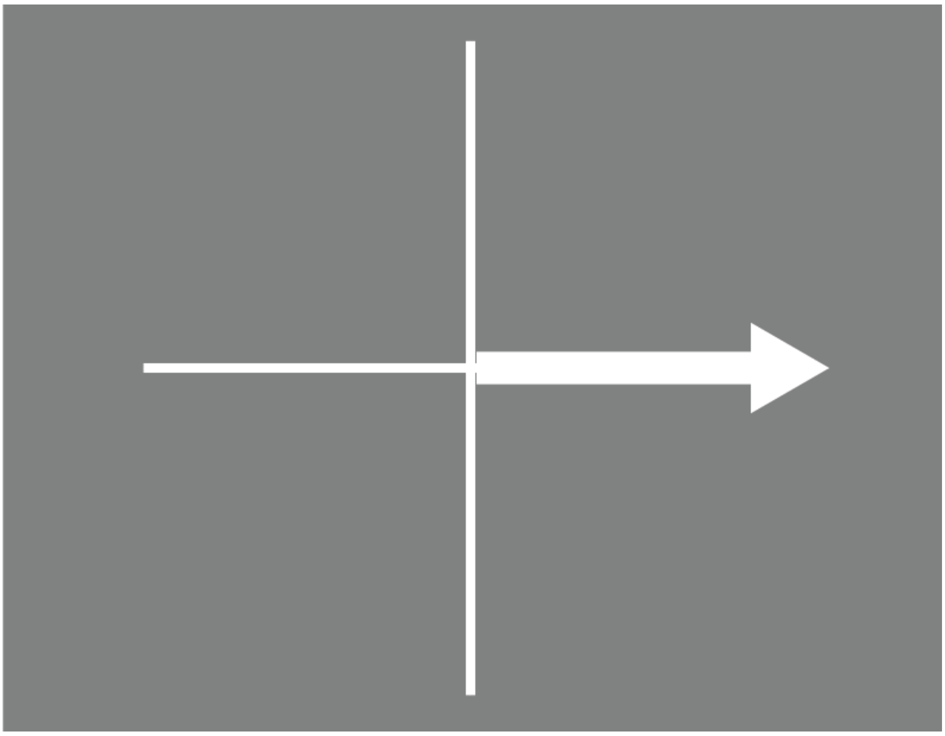


Execução movimento mão direita.

Imaginação movimento mão esquerda.



Imaginação movimento mão direita.



Imaginação movimento terceiro braço.

-Na imaginação, tente imaginar a sensação de estar fazendo o movimento solicitado (abrir e fechar a mão). Para o terceiro braço, imagine um membro adicional que se origina da parte central do tórax e executando a mesma ação.

-Aplicação do questionário final: ao final do experimento, você vai responder algumas perguntas relacionadas ao teste. Qualquer feedback é bem-vindo.

Se você tiver alguma dificuldade ou mal estar durante o experimento você deve informar para que o experimento seja interrompido.

Bom teste e obrigado!

☐ Send me a copy of my responses.

APPENDIX C — NASA-TLX QUESTIONNAIRE

NASA TLX & SEQ

* Required

1. **User ID** *

2. **Task** *

Fontes de Sobrecarga

A avaliação que você está prestes a fazer é uma técnica que tem sido desenvolvida pela NASA para avaliar a importância relativa de seis fatores na determinação da carga de trabalho ("workload") em uma dada tarefa:

DEMANDA MENTAL - Quanta atividade mental e perceptual foi exigida (ex.: pensando, decidindo, calculando, relembrando, olhando, buscando, etc.)? A tarefa foi fácil ou exigente, simples ou complexa, exata ou flexível?

DEMANDA FÍSICA - Quanta atividade física foi exigida (ex.: empurrando, puxando, girando, controlando, ativando, etc.)? A tarefa foi fácil ou exigente, devagar ou apressada, preguiçosa ou energética, descansada ou trabalhosa?

DEMANDA TEMPORAL - Quanta pressão você sentiu com relação ao tempo devido ao andamento ou ritmo em que as tarefas ou etapas da tarefa aconteceram? O ritmo foi devagar e sem pressa ou rápido e frenético?

ESFORÇO - Quão duro você tem que trabalhar (mentalmente e fisicamente) para atingir seu nível de desempenho?

DESEMPENHO - Quão bem sucedido você pensa ter sido em atingir os objetivos da tarefa estabelecidos pelo experimentador (ou por você mesmo)? Quão satisfeito você foi com sua performance ao atingir esses objetivos?

NÍVEL DE FRUSTRAÇÃO - Quão inseguro, desencorajado, irritado, estressado e aborrecido versus seguro, grato, contente, relaxado, e complacente você se sentiu durante a tarefa?

3. **Selecione o fator que representa o mais importante contribuinte para a sobrecarga na tarefa que você acabou de fazer** *

Mark only one oval per row.

	A	B
(A) Dem. Física ou Temporal (B)	⬭	⬭
(A) Dem. Temporal ou Frustração (B)	⬭	⬭
(A) Desempenho ou D. Temporal (B)	⬭	⬭
(A) Frustração ou Dem. Mental (B)	⬭	⬭
(A) Frustração ou Esforço (B)	⬭	⬭
(A) Dem. Temporal ou Mental (B)	⬭	⬭
(A) Dem. Física ou Frustração (B)	⬭	⬭
(A) Esforço ou Dem. Física (B)	⬭	⬭
(A) Dem. Física ou Desempenho (B)	⬭	⬭
(A) Dem. Mental ou Física (B)	⬭	⬭
(A) Desempenho ou Frustração (B)	⬭	⬭
(A) Dem. Mental ou Esforço (B)	⬭	⬭
(A) Esforço ou Desempenho (B)	⬭	⬭
(A) Desempenho ou Dem. Mental (B)	⬭	⬭
(A) Dem. Temporal ou Esforço (B)	⬭	⬭

Magnitude da Sobrecarga

4. **Quão mentalmente exigente foi a tarefa?** *

Demanda Mental

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Muito Baixa	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muito Alta

5. **Quão fisicamente exigente foi a tarefa?** *

Demanda Física

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Muito Baixa	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muito Alta

6. **Quão corrido ou apressado foi o ritmo da tarefa?** *

Demanda Temporal

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Muito Baixa	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Muito Alta

7. **Quão bem sucedido você foi em realizar o que te foi pedido para fazer?** *
Desempenho
Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Perfeito	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Falho

8. **Quão duro você teve que trabalhar para alcançar seu nível de desempenho?** *
Esforço
Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Muito Baixo	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Muito Alto

9. **Quão inseguro, desencorajado, irritado, estressado, e aborrecido você estava?** *
Frustração
Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Muito Baixa	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Muito Alta

10. **Comentários**
(opcional)