THIAGO BASSANI

DESIGN OF A BCI SYSTEM USING EEG SIGNAL ANALYSIS WITH CONTINUOUS WAVELET TRANSFORMATION AND NAÏVES BAYES CLASSIFIER

Dissertação apresentada ao Programa de Pós-Graduação em Informática Aplicada da Pontifícia Universidade Católica do Paraná como requisito parcial para obtenção do título de Mestre em Informática Aplicada.

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Área de Concentração: *Descoberta de Conhecimento e Aprendizagem de Máquina.*

Orientador: Prof. Dr. ....Julio Cesar Nievola

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Esta página deve ser reservada à ata de defesa e termo de aprovação que serão fornecidos pela secretaria após a defesa da dissertação e efetuadas as correções solicitadas.

O sonho é ver as formas invisíveis
da distância imprecisa, e, com sensíveis
Movimentos da esp'rança e da vontade,
Buscar na linha fria do horizonte
A árvore, a praia, a flor, a ave, a fonte –
Os beijos merecidos da Verdade.
Fernando Pessoa

It is possible to believe that
all the human mind has ever accomplished
is but the dream before the awaking.
H. G. Wells

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Contents

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List of Symbols

$W_{\cdot}(.)$	Continuous Wavelet Transformation
$x_{\cdot}$	Time series, or vector
t	A time stamp
ψ	Wavelet function
δt	Time spacing of a time series
s	Wavelet scale
N	Number of points in the time series
n	Each element in the time series
$\mathbb{C}$	Set of Complex numbers
$\mathbb{R}$	Set of Real numbers
$\psi(t)$	Wavelet function defined by the time parameter
i	denotes the imaginary unit, $(-1)^{1/2}$
ω_0	an non-dimensional frequency parameter of the Morlet function
$\|W_n(s)\|^2$	Wavelet power spectrum
$R^2(.)$	Wavelet Coherence
$S(.)$	Smoothing operator
$PC(.)$	Phase-coherence
$\Im\{.\}$	Imaginary part of a complex number
$\Re\{.\}$	Real part of a complex number
δj	The scale spacing of a scale series
j	Scale series
C_δ	The reconstruction parameter factor
$P(\cdot\|\cdot)$	Conditional probability
C_k	The class specified by the parameter *k*
p	Probability
b	The bit rate measurement

List of Abbreviations

ANC	ACTIVITY OF NEURAL CELL
ALS	AMYOTROPHIC LATERAL SCLEROSIS
AT	ASSISTIVE, OR AUGMENTATIVE, TECHNOLOGY
AR	AUTOREGRESSIVE COEFFICIENTS
BLDA	BAYESIAN LINEAR DISCRIMINANT ANALYSIS
BI	BRAIN INTERFACE
BCI	BRAIN-COMPUTER INTERFACE
COI	CONE OF INFLUENCE
CWT	CONTINUOUS WAVELET TRANSFORMATION
T-CWT	CWT AND STUDENT'S T-STATISTIC
DWT	DISCRETE WAVELET TRANSFORMATION
EPFL	ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE
EEG	ELECTROENCEPHALOGRAPHIC
ECOG	ELETROCORTICOGRAM
ERO	EVENT-RELATED OSCILLATIONS
ERP	EVENT-RELATED POTENTIAL
FMRI	FUNCTIONAL MAGNETIC RESONANCE IMAGING
FN	FALSE NEGATIVES
FP	FALSE POSITIVES
FIR	FINITE IMPULSE RESPONSE FILTER
FT	FOURIER TRANSFORMATION
IIR	INFINITE IMPULSE RESPONSE
KDD	KNOWLEDGE DISCOVERY IN DATABASES
LDA	LINEAR DISCRIMINATE ANALYSIS
MEG	MAGNETOENCEPHALOGRAPHY
NBC	NAÏVE BAYES CLASSIFIER
PC	PHASE-COHERENCE
SAWP	SCALE-AVERAGED WAVELET POWER
SCP	SLOW CORTICAL POTENTIAL
TN	TRUE NEGATIVES
TP	TRUE POSITIVES
VEP	VISUAL EVOKED POTENTIAL
WC	WAVELET COHERENCE
WEKA	WAIKATO ENVIRONMENT FOR KNOWLEDGE ANALYSIS

Resumo

Uma das questões mais importantes na interface de computador-cérebro é a análise de padrões cerebrais, geralmente representados por sinais elétricos. Este trabalho tem como objetivo introduzir uma ferramenta de mineração de dados para sinais de EEG, analisando os padrões no plano tempo-freqüência utilizando a transformada contínua de odeletas. Este trabalho também aspira aperfeiçoar a análise de sinal eletroencefalográfico, e sua melhor classificação, e possivelmente, aumentar a eficiência do sistema de interface computador-cérebro aumentando sua velocidade e acurácia. Nesta pesquisa a tranformada contínua de odeleta permite uma maior legibilidade de informações sobre sinais de eletroencefalográfico analisado qualitativamente. Os resultados sugerem que a metodologia proposta seja capaz de identificar padrões significativos com freqüências e tempo específicos, relacionadas com as atividades cerebrais do usário. Em um segundo momento nesse trabalho busca-se classificar esses padrões usando o classificador ingênuo de Bayes. Posteriormente, a velocidade e a precisão dos resultados apresentados por essa classificação são analisados. E como resultado o método apresentado obteve 61 bit/min de velocidade e 70% de acurácia, aumentando-se significativamente a velocidade em relação ao estado da arte, pois foram utilizados segmentos menores de sinais, possibilitando uma resposta mais rápida. Todavia, a precisão foi reduzida em relação ao estado da arte. Adicionalmente o ferramental desenvolvido neste projeto cria novas possibilidades em pesquisas de sinais fisiológicos e análise de série de temporais não-estacionárias.

Palavras-Chave: Analise de Padrões, Classificação, Processamento de Sinas, Interface computador máquina.

Abstract

One of the most important issues in brain-computer interface (BCI) is the analysis of patterns in brain states generally represented by electrical signals. The main objective of this work is to present an exploratory approach on electroencephalographic (EEG) signal, analyzing the patterns in the time-frequency surface. This work also aims to optimize the EEG signal analysis through the improvement of classifiers and, eventually, of the BCI performance. In this paper a novel exploratory approach for data mining on EEG signal based on continuous wavelet transformation (CWT) and wavelet coherence (WC) statistical analysis is introduced and applied. The CWT allows legibility of signal information content to represent time-frequency patterns illustrated in WC qualitative analysis. Results suggest that the proposed methodology is capable of identifying regions in time-frequency spectrum during the specified task on BCI. Furthermore, an example of a region is identified, and the patterns were classified using a Naïve Bayes Classifier. This innovative characteristic of the process justify the feasibility of the proposed approach for another data mining applications. It can open new physiologic researches in this field and researches in different non-stationary time series analysis.

Keywords: Pattern analysis, Classification, Signal Processing, Brain Computer Interface.

Chapter 1

Introduction

1.1 Motivation

From the first moments in this world, a human initiates a communication exchange, using different interfaces, such as the cry vocalization of a newborn infant, after a normal childbirth. Communication is the basis of human development, it allows us to interact with others, express ideas, desires, feelings etc. However, for individuals with the locked-in syndrome, the communication is a difficult challenge, as for the amyotrophic lateral sclerosis (ALS) disease. Patients with ALS lose the autonomy by a progressive neurodegenerative disease that causes the loss of control over voluntary muscles. For these cases the only interface remaining for communication is their brains activity, and the Brain-Computer Interface (BCI) field proposes to allow users with motor disabilities to communicate, improving the life quality of the lock-in patients.

The BCI uses electrophysiological measurements of brain activity to enable communication with external devices, as computers and prosthesis [Bostanov, 2004].

Generally, electrical signals represent brain states, which are organized in large dataset. In this field the pattern analysis is an essential process to understand the brain-states features underlying these datasets. The state-of-the-art describes various algorithms to identify these patterns. Nonetheless, comparison of these algorithms is a difficult task given the diversity of BCI systems for different aspects such as target application, neuromechanism used, amount of data tested, number of subjects experimental paradigms, and other specifications. The BCI represents a novel interdisciplinary knowledge field, with many challenges for researchers to provide a step towards the current state-of-the-art. On this way, a strategic contribution for this field is a useful and understandable pattern extraction method for knowledge discovery in databases (KDD).

The KDD becomes an important subject for academia, industry and that interdisciplinary field in particular. KDD is a process of extraction of novel, useful and understandable patterns from a collection of datasets. For the extraction of this novel information, a powerful technique current applied is the continuous wavelet transformation (CWT). Although wavelet transformations have attracted much attention in the data mining community, there has been no defined exploratory approach, to produce understandable patterns for futures studies in the current field of EEG. The studies of an exploratory approach based on CWT will also be a future promising contribution for applications beyond BCI systems, as Epilepsy and Alzheimer pattern recognition.

1.2 Focus

The target population is disabled patients, although few works concern this population for BCI systems validation. Nonetheless, validating algorithms with datasets from disabled subjects is crucial, simply because disabled subjects are the target population for work. The current work uses the EEG dataset acquired and organized by Hoffmann et al [Hoffmann et al., 2008]. They described a BCI system based on a six-choice P300-based system. Four disabled and four able-bodied subjects tested the system on four different sessions, with six individual runs, one for each possible choice of the system. Hoffmann et al (2008) made the dataset available for downloading on the website of the BCI group in École Polytechnique Fédérale de Lausanne (EPFL) (http://bci.epfl.ch/p300).

The BCI systems include diverse applications, although this dissertation focuses on systems that record and analyze signals from brain noninvasively. A particularly popular noninvasive method used on this work is the electroencephalogram (EEG), which is an electric potential measurement of the brains scalp, at a resolution about microvolts and milliseconds. Physicians know this measurement method as a low risk procedure, comparing with invasive electrodes implanted by a surgical procedure in the motor cortex. Although, this noninvasive method decrease the signal-to-noise ratio, demanding efficient signal processing and feature extraction methods.

According to Wolpaw et al (2002) and recently Bashashati et al (2007) the BCI systems could be categorized in seven majors groups: sensorimotor activity, P300, visual evoked potential (VEP), slow cortical potential (SCP), activity of neural cell (ANC), response to mental task and multiple neuromechnisms. This dissertation works with the P300 group defined as an infrequent or particularly significant auditory, visual, or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke in the EEG over the parietal cortex a positive peak at about 300 ms after the stimulus is received (Allison and Pineda 2003).

Hoffmann et al (2008) captured the activity of the brain using the EEG scalp electrodes with the 10-20 standard, a widely used noninvasive technique. It acquired a brain electrical signal that has differences of potential in the range (0 - 100μV). With such small amplitude, the contamination of EEG data during the recording process is common. Therefore, an artifact removal and filtering procedure is necessary before the analysis of EEG signals. Even so, the signal must be filtered to avoid contaminations, and focus in a particular oscillation frequency. Such oscillation relies on the neurophysiologic observations, that large populations of neurons in the respective cortex are sending in rhythmical synchrony when a subject is not engaged with one of his limbs, i.e. movements, tactile senses, or just mental introspection [Lemm et al., 2005].

This work uses Mason et al (2007) designing model for compare different application, and also define the innovative aspect of the current dissertation, illustrated on figure 1.1. This model includes a variety of process, and on chapter 2 it will be detailed. However, the Feature Extraction and the Classification process are the main focus of this work, and in the referenced figure they are the two boxes painted on black with white words. These two processes represent are important for BCI system, they represent the knowledge needed to perform the fill the ability gap between the user and the device.

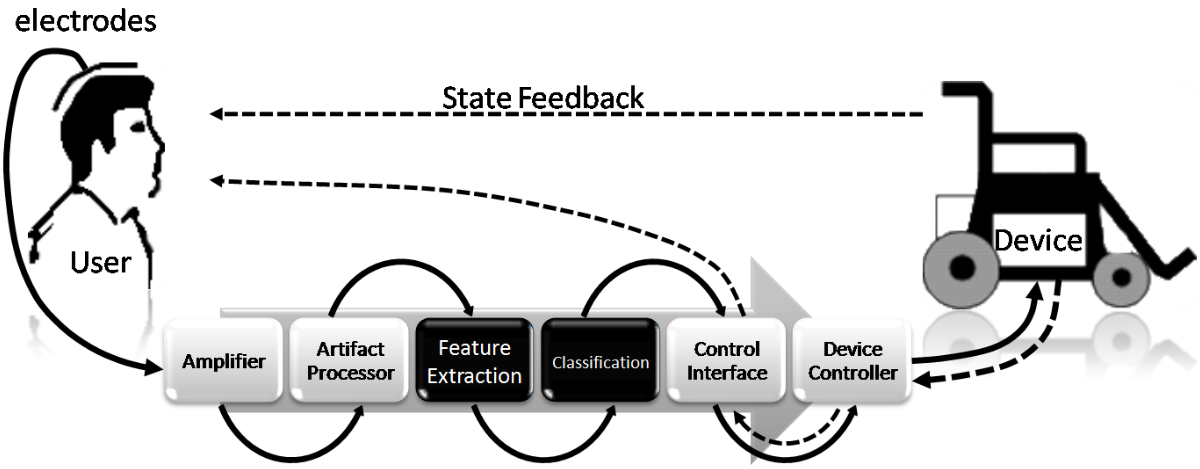

Figure 1.1: A functional model of a BCI system.

1.3 Main Contributions

This work intent to design and apply a framework to analyze time-frequency patterns illustrated on CWT and WC qualitative analysis, and classifies those patterns through a quantitative measurement extracted from the CWT to analyses the electroencephalographic (EEG) signal patterns. The objective of such framework is to introduce and apply an exploratory approach for data mining based on EEG signal provided from users with motor disabilities. Thus research intent also to improve the results of classification and eventual BCI performance. A vital feature of BCI system is the capability to distinct between the attended and ignored events with speed and accuracy. These characteristics differentiate artificial pattern recognition systems applied on BCI. For that reason, this research intent to improve the bit rate measurement, as a speed parameter, with an acceptable accuracy. Therefore, the accuracy is not the only characteristic of the classifier analyzed. The speed of communication is another desirable characteristic for BCI systems.

1.4 Original Contributions

The original contributions of this Dissertation are [Bassani and Nievola, 2008]:

- The CWT significance and confidence method of analysis developed by Torrence and Compo applied on atmospheric time series was extended for EEG signals [Torrence and Compo, 1998]. The geophysical time series was modeled as a univariate lag-1 autoregressive red noise signal (Markov process). However, this work analyzes the EEG signal of BCI application with another statistical analysis based on the Monte Carlo method. Each EEG signal segment was processed with CWT, and this transformation was applied on Monte Carlo method to establish the significance levels and confidence interval for the wavelet spectrum;
- The significance level and confidence interval allow the development of a novel exploratory framework for BCI systems, based on CWT with WC measurement;
- This work also presents an experimental demonstration of the usefulness of the developed framework for BCI.

1.5 Organization

This work is organized into four chapters, beside this introductory one. The second chapter introduces BCI, and presents the principle of EEG signals, where BCI communication relies. This chapter also presents some EEG features, and the features extraction method correlated with this research. Chapter three deals with the methodology applied on this work. The dataset organization, the FIR filter process, the CWT method, and the Naïve Bayes Algorithm are also presented on that chapter. All experimental results are given in chapter four with specifications and parameters used. And finally, on chapter five a discussion of the results is presented followed by the final conclusions and further works.

Chapter 2

Review of BCI Wavelet Analysis

2.1 Introduction

The brain-computer interface is a system that contrast with other interface by the use of brain signals to provide a non-muscular communication channel. This interface can allow locked-in patients to communicate with others, or to control their environment. Many researchers are currently investigating this knowledge field, and the number of publications had strongly increased during the last few years. Therefore, many reviews papers of this study field were consulted and referenced in this work, as Wolpaw et al. [Wolpaw et al., 2002], Bashashati el al. [Bashashati et al., 2007], Lebedev and Nicolelis [Lebedev and Nicolelis, 2006], Lotte et al. [Lotte et al., 2007], Birbaumer and Cohen [Birbaumer and Cohen, 2007], and Mason et al. [Mason et al., 2007]. The technical terminology of Mason et al is the chosen reference used on this work to organize the state-of-the-art, and asserting novelty and inventive step of the proposed methodology. This technical terminology provides an objective evaluation among applications as a general framework.

The first section introduces BCI and a briefly overview of the main issues of the general framework. The next section introduces the EEG signal with the recording technique, and some concerning its use. Section 2.4 and section 2.5 introduce previous studies of EEG patterns related with neurophysiologic activities. On section 2.6 the method of extracting and translating EEG features is discussed, and the conclusion in section 2.7 closes this state-of-the-art chapter.

2.2 Brain Computer Interface

In the framework adopted [Mason et al., 2007], a subject with physical limitations desires to interact with other ones, or with the environment that surrounds him or her. These so called limitations, produces a gap between the person abilities and those abilities required for interaction. A proposed assistive, or augmentative, technology (AT) provides the additional functionality that he requires to perform the interaction, or activity, as illustrated in fig. 2.1. The AT allows an individual with physical limitations to answer the stimuli of the environment and receive an appropriated feedback from their interaction, or even interact spontaneously.

The brain interface (BI) is an AT, and it provides additional functionality to a target population. In this context the BI is described in this research as a sequence of three components: a BI Transducer, a Control Interface, and an Assistive Device, as depicted in figure 2.2. The focus of this work is specifically the BI Transducer component. This component, like the previous one, is represented by a more detailed model, as shown in figure 2.3. Following the framework more details of the taxonomy components and sub-components used are presented in Table 1.1, which also presents the techniques that the current work applies classified following Mason et al.

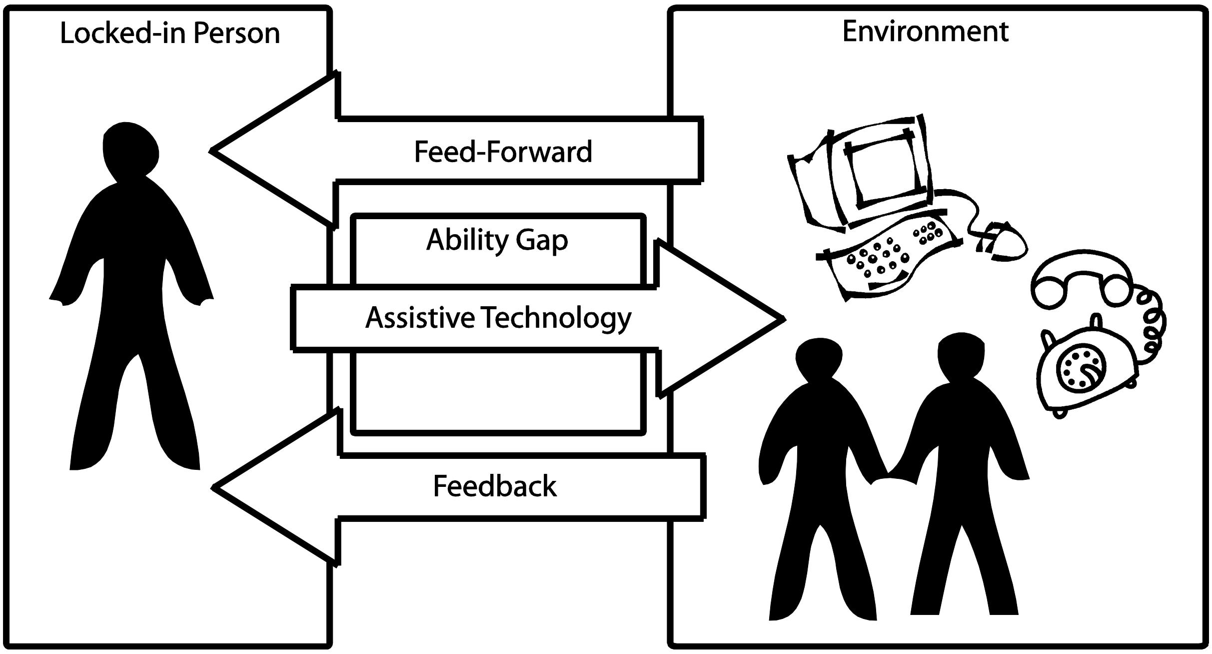

Figure 2.1: Assistive Technology solution adapted from Mason et al [Mason et al., 2007].

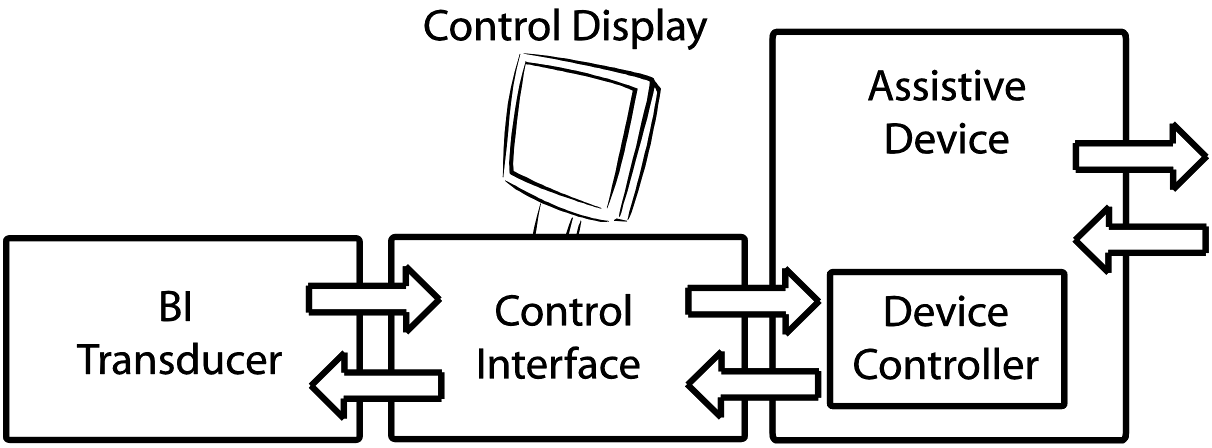

Figure 2.2: A functional model of 3-component BI AT based on Mason et al [Mason et al., 2007].

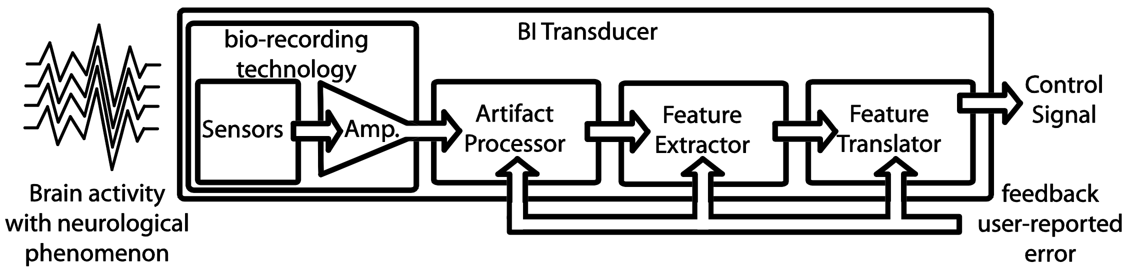

Figure 2.3: A functional model of a BCI system based on Mason et al [Mason et al., 2007].

Table 2.1: The BI transducer design attributes, and brief description of each attribute, and the techniques applied on this work. According on Mason et al [Mason et al., 2007].

BI Transducer Attribute	***Description***	***Current Work***
Target Population	**The target population defines on general terms the set of users of the system.**	**Full paralysis**
Target Activity	**The activity intended to be performed by the Target Population.**	**Communication with people**
Transducer Design Model	**The general architecture used for the transducer design. There are three primary design models: exogenous (an external stimulator in used to evoke response from the user), endogenous (no stimulator is required as control signals are generate internally) and modulated response (a variation on exogenous designs).**	**Exogenous**
Bio-recording Technology	**This attribute refers to the class of equipment (sensors, amplifiers, converters and filters) used to measure a person's brain activity in a BI Transducer. Researchers have used EEG, ECoG, custom implanted microelectrode arrays and amplifiers, and functional near infrared. Others have discussed possible fMRI and MEG solutions, but the practicality of these later approaches is suspect.**	**EEG**
Neurological Phenomenon	**This attribute refers to the phenomenon (or phenomena) used to control a BI Transducer. For example, a P300 response in EEG to an oddball stimulus is a well-studied phenomenon employed in several BI Transducers. Another well-known phenomenon is the increase in neural firing rates measured in microelectrodes as neural activity increases.**	**Mu, alpha, beta or other rhythm power**
Sensor Placement	**Sensor Placement identifies the general location of bio-sensors used in a BI Transducer.**	**Over multiple cortical areas**
Artifact Processor	**A component of a BI Transducer that removes artifact from the input signal. Note, many transducer designs do not include artifact processing.**	**None**
Stimulator (and Stimulus Mechanism)	**The Stimulator and its associated Stimulus Mechanism (e.g., strobe lights or flashing areas of a screen) are used to stimulate the user and evoke a response in exogenous or modulated-response transducers. A wide variety of stimuli methods have been used and are directly related to the neurological phenomenon.**	**Flashing area of a screen**
Feature Extractor	**A component of a BI Transducer that translates the (artifact-free) input brain signal into a value correlated to the neurological phenomenon. The output value is referred to by the Pattern Recognition community as a ''feature vector''. The function of this component is sometimes referred to as noise reduction, filtering, preprocessing or spike detection/sorting depending on the background of the investigator.**	**Wavelet Transform**
Feature Translator	**The component of a BI Transducer that translates the feature vector into a useful control signal. Researchers working with discrete transducer outputs often refer to this component as a Feature Classifier or Classifier as these terms are more specific. For similar reasons, researchers working with implanted microelectrodes use the term ''decoding function'' (or something similar).**	**Naïve Bayes**
Output	**The type and dimensionality of a BI Transducer output. For example, 2-state discrete output, or one-dimensional, continuous amplitude digital signal.**	**6-state**

2.3 Electroencephalogram Signal Acquisition

A BI device should have a low cost, non-invasive, practical and efficient procedure. The electroencephalogram (EEG) could potentially complete this interface requirements. This method captures the brain activity through electrical potential difference between electrodes, for example at the head scalp. The EEG signal contains valuable information about the cortex activity, for example the visual awareness [Struber and Herrmann, 2002], and motor activity [Bland et al., 2006].

The EEG represents the extracellular activity potential sum of a large group of neurons. Caton, on 1875, realized the first record of an electrical activity of the brain from rats and monkeys [Caton, 1875]. However, it was only on 1929 that Hans Berger applied such method on humans [Berger, 1929]. Berger initiated his study on 1924, using galvanometers, and he demonstrated the different characteristics in the brains signal such as: the alpha rhythm, some evidences of neurological disorders, and the sleep stages.

The electric potential could be measured between electrodes, or using specific reference electrodes, The EEG record is acquired through high conductivity electrodes inside or outside the brain [Knight, 2003]. The invasive techniques place the electrodes directly inside the cortex, for example using the eletrocorticogram (ECoG) method. This technique provides signals with superior signal-to-ratio, nonetheless the invasive surgery procedure increases the costs of the application. The most common noninvasive technique presented is the scalp EEG, which set the electrodes at the head skin. The signal of EEG is composed basically by the sum of millions of postsynaptic electrical potentials in the cortex.

The electrodes of the EEG signal are organized on a standard placement called *International System 10-20*, the position of each electrode is exemplified in figure 2.4. This system has two electrodes positioned at each auricular side on the ear (A1 and A2). These two electrodes are used for reference, since the potential remains fairly constant at the ear lobes. The other electrodes are identified with capital letters indicating the respective cortical zone: Frontal (F), Central (C), Parietal (P), Temporal (T), Occipital (O), and Frontopolar (Fp). The odd numbers with the capital letter indicate electrodes on the left side of the head, the even numbers on the right side. The letter *"z"* describes the electrodes in the midline of the head.

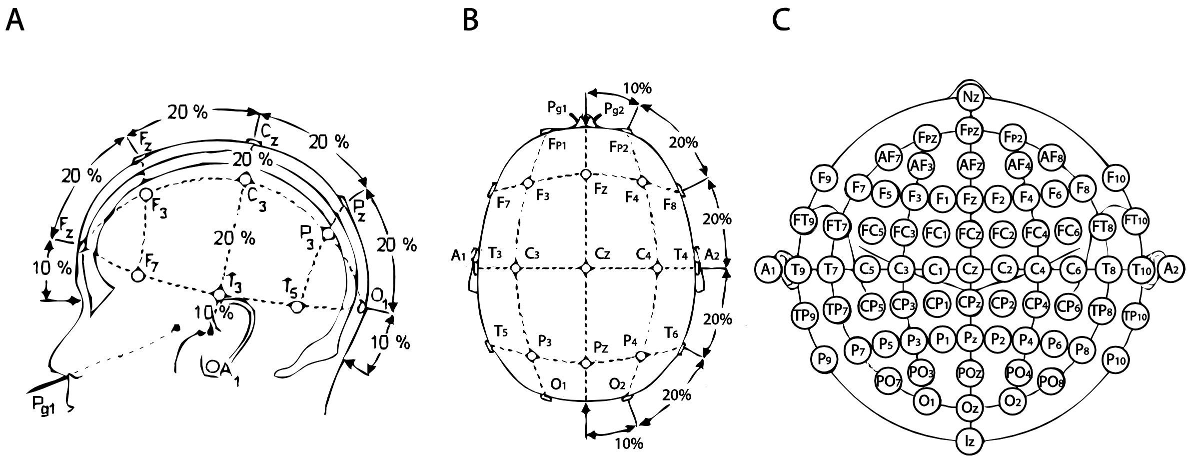

Figure 2.4: The placement of electrode of the International System 10-20. Based on: [Hoffmann, 2007].

A high risk of scalp EEG analysis is the potential interference from other biological electrical signal, or external signals. These other signals combined with the focus neuronal target rhythms difficult the EEG evaluation, as shown on figure 2.5. The noise produced by artifacts could be injected on the EEG signal from different sources during the EEG recording process: eye blink, eye movement, electrical source noise, muscle activity, pulse. For example, the averaged electrical amplitude of an EEG signal record is represented between -50 μV to +50 μV, a single eye blink could generate a signal with 100 μV [Knight, 2003]. This single eye blink on this example could invalidate an EEG recorded.

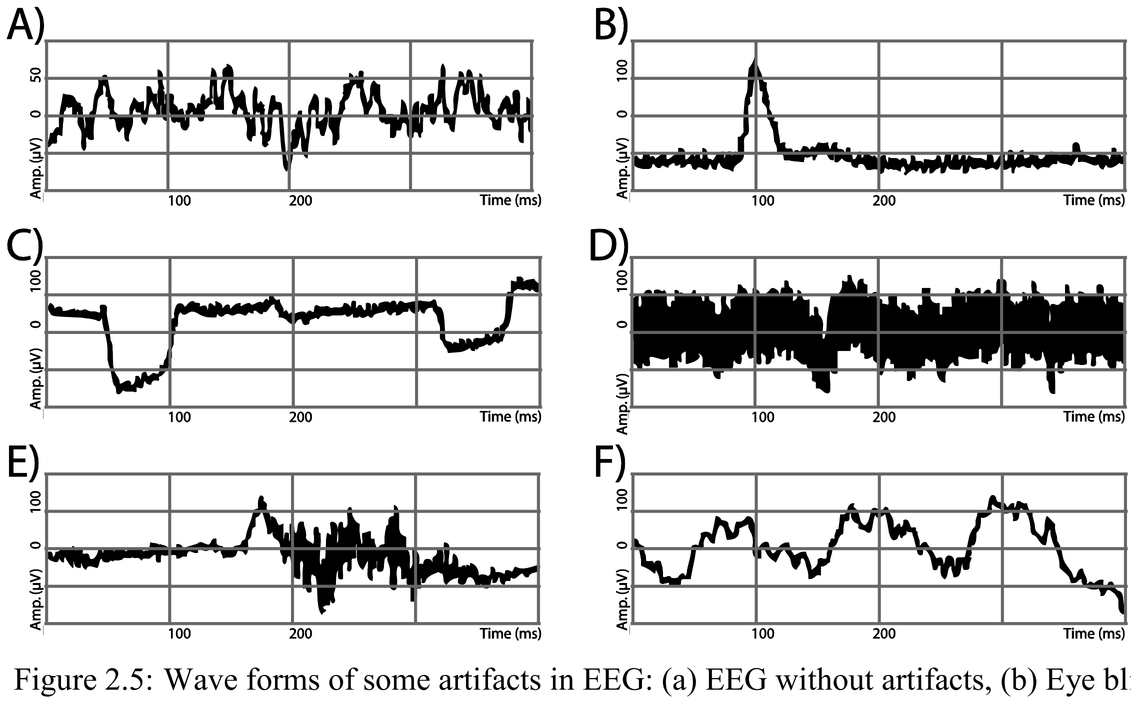

Figure 2.5: Wave forms of some artifacts in EEG: (a) EEG without artifacts, (b) Eye blink, (c) Eye movement, (d) Noise with 60 Hz, (e) muscle activity, (f) pulse. Adapted from: [Knight, 2003].

2.4 Event-Related Potential

A particular “event” or an external stimulus causes an involuntary brain activity response, called Event-Related Potential (ERP). The scalp EEG captures these responses when the patient does a specified task. For the BCI system used on this work, the target stimulus appears rarely, while nontarget stimuli appear more often. In this system six flashing images stimulate event-related Visual Evoked Potential (VEP), displayed on a Personal Computer controlled Liquid Cristal Display monitor. Patients are asked to count to a unique target image on each experimental run. The visual stimulus of this image causes the VEP, and the averaged over multiple trials has labeled components, positive and negative electrical waves. These cortical events in turn are hypothesized to be closely related to psychological processes. The literature defines a set of components studied previously: P1, N1, P2, N2 and P300 [Lee et al., 2006]. Donchin and co-workers applied successfully these components in BI spelling device [Donchin et al., 2000]. The first cortical area to receive sensory input have preeminently early components, labeled exogenous potentials, e.g. P1, N1, P2, N2, shown on Figure 2.6. They represent neural activity in the sensory pathways that are closely related to the physical properties of the stimulus. The later occurring potentials in Figure 2.6, e.g. N2, P3 and N400, are labeled endogenous potentials. These potentials are affected by psychological processes, such as discrimination difficulty, attention, expectancy, and intention. They are unrelated to physical changes in the stimulus, and may occur in the absence of external stimulation. These endogenous potentials have also interest to cognitive psychophysiology, because they are related to complex psychological processes that occur during cognitive activity.

The most commonly studied ERP is the P300. This positive deflection in the EEG occurs about 300 ms after the stimulus onset. The P300 is commonly recorded during an odd-ball paradigm, involving a target and a non-target stimulus [Polich and Kok, 1995]. Unfortunately, this approach may be slow as one character/minute. The signal-to-noise ratio of the scalp EEG requires improvements.

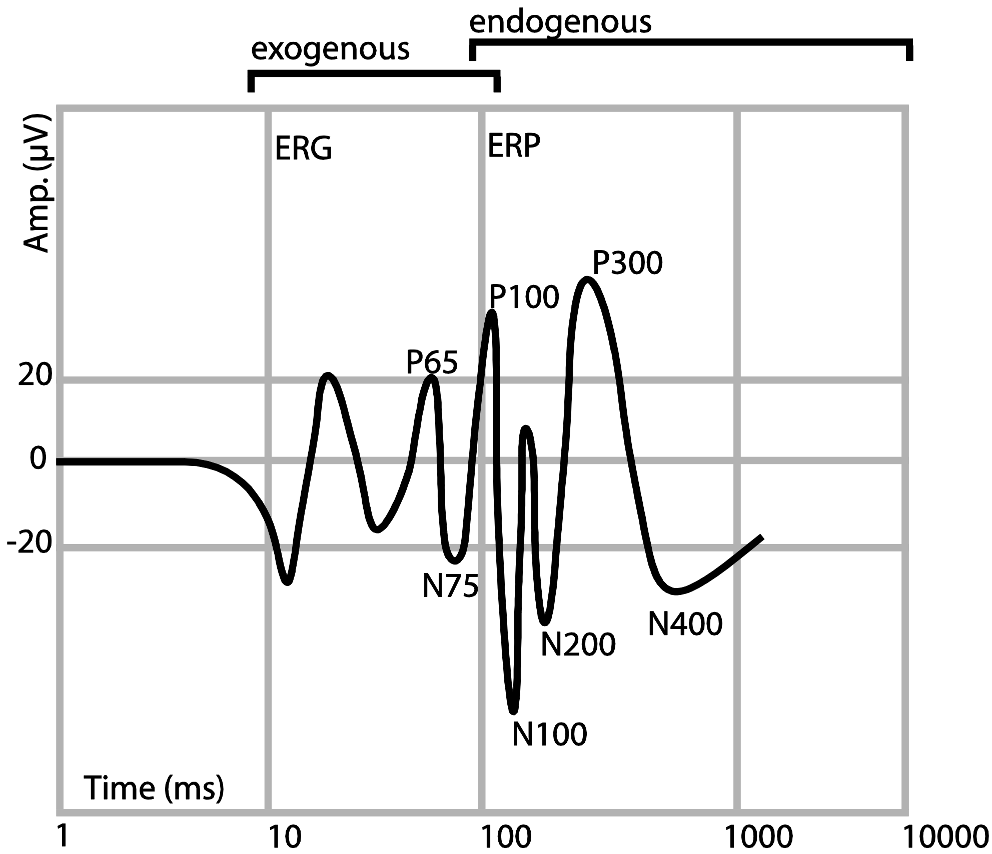

Figure 2.6: An Illustration of the exogenous and endogenous components. Source: (Knight, 2003).

2.5 Event-Related Oscillations

The oscillatory brain activity in the EEG could be analyzed with different frequency bands or rhythms. This approach is called Event-Related Oscillations (ERO) and the rhythms could be visualized on Table 2.2. This method is suited to temporal and spatial characteristics of continuous wavelet analysis method. Basar et al, 1999, convincingly demonstrated that assessing specific oscillations frequencies can often yield insights into the functional cognitive correlations of ERP signals [Basar et al., 1999]. Although the evoked oscillations are not visible due to low amplitude and high frequency, it usually results from sensory events, e.g. visual, auditory and somatosensory.

Table 2.2: The event-related Potentials and the associated frequency band, period band and oscillation.

Frequency Band	*Period Band*	*Oscillations*	*Correlated ERP Components*
0 – 4 Hz	250ms – 500ms	**Delta**	**N3, P300**
4 – 8 Hz	125 – 250 ms	**Theta**	**N2, P2**
8 – 12 Hz	80 – 125 ms	**Alpha**	**N1, P1**
12 -30 Hz	30 – 80 ms	**Beta**	**Exogenous**
30 – 80 Hz	30 – 12 ms	**Gama**	**Exogenous**

The evoked delta and theta oscillations represent slow potentials in ERP, e. g. P300 and N3. These oscillations are not identical to those in raw EEG signal which is related to deep sleep, hypnosis and coma [Steriade et al., 1993]. These oscillations appear during motor tasks [Bland et al., 2006].

The alpha rhythm presents bursts mostly related with a sensory stimulus. The alpha activity has been associated with memory processes [Klimesch, 1997], attention [Klimesch et al., 1998], and visual awareness [Struber and Herrmann, 2002].

The beta activity is associated with cognitive processes like memory rehearsal, sensory and motor processes [Tallon-Baudry et al., 2001]. Haenschel et al assumed that beta oscillations are induced by faster gamma oscillations and maybe they induce slower alpha oscillations [Haenschel, 2000].

The gama oscillations are correlated with binding phenomena [Muller et al., 1997], perceiving meaningful objects [Keil et al., 1999], attention [Debener et al., 2003] and maybe even consciousness [Llinas and Ribary, 1993]. These frequencies could be described even by higher frequencies, e. g. 600 Hz [Curio, 1999].

2.6 Related Studies

The recognition of dissimilarities between target and non-target EEG response by the presented stimuli is a pre-requirement for a reliable P300 Speller system. Such dissimilarities could be investigated through the EEG coherence measurement, as a well-established tool to analyze the linear relationship between two signals [Stam and van Dijk, 2002] [Micheloyannis et al., 2005]. The classical Fourier analysis requires stationary feature within each window analyzed, which is not found on brain dynamical signal of EEG. A more appropriate approach, applied on this research, is the Continuous Wavelet Transformation (CWT). Such technique analyses fractal structure in time series that contain non-stationary power at different frequencies [Kantz and Schreiber, 1997] [Grinsted et al., 2004], so the dissimilarities between target and non-target EEG signal are recognized.

What distinguishes the Discrete Wavelet Transformation (DWT) and the CWT is the scale shift domain, which is in $\mathbb{Z}^+$ or in $\mathbb{R}^+$ respectively, although both transformations allow working with discrete sampled time series, like the EEG signals. These characteristics are valid with different wavelet functions: the use of orthogonal basis implies in the use of DWT, while a non-orthogonal wavelet function can be used with either the DWT or CWT [Farge, 1992]. For analysis purposes, the orthogonal CWT is better suited because its redundancy allows good illustration of signal information content [McKhann et al., 1984], in contrast to the DWT, which does not permit such analysis. The CWT also uses complex wavelet basis functions that capture the amplitude and phase information from the signal [Stam and van Dijk, 2002].

Reviewing the literature, few works were found related to the present study. Lachaux et al (2002) studied and applied single-trial brain signals using Wavelet Coherence (WC) method of CWT [Lachaux et al., 2002], showing its statistical properties and comparing it with Fourier coherence on this particular time series analysis. They presented a qualitative approach to compare two non-stationary neural signals, although for BCI system a quantitative measurement is still needed for classification purposes.

Bostanov et al (2004) applied a method based on CWT and Student's t-statistic, named t-CWT method, on single-trial ERPs signal [Bostanov, 2004]. The first steps calculate the CWT of each signal in each channel, using the Mexican Hat wavelet, and compute the mean and variance of each group. The next step applies the Student's t-statistic to measure the distance between each trial of the two groups: the target and non-target (P300 category). The final step uses a pattern recognition system called the Linear Discriminate Analysis (LDA). This approach introduces a quantitative measurement based on the CWT and Student's t-statistic method for pattern classification.

Sakkalis et al (2006) applied a method to analyze schizophrenic brain activity and test a known hypothesis of disconnection and working memory deficits [Sakkalis et al., 2006]. They used the WC with graph theory measurements to evaluate distance functional connectivity in complex neural network. The results presented are graph networks used to distinguish healthy from schizophrenic disturbance connections. The WC method used is capable to reveal novel patterns in neural signals.

Hoffmann et al (2005) first applied a Gradient Boosting with an Ordinary Least Squares (OLS), a regression method, to detect the P300 in a spelling device [Hoffmann et al., 2005]. This classification method produces a precision between 90% and 100% with the dataset of the BCI Competition 2003. At 2008 they presented a work with disabled users' dataset, using a Bayesian Linear Discriminant Analysis (BLDA) with a standard algorithm [Hoffmann et al., 2008]. The classification accuracy was 100%, and the bitrates for the disabled subjects was between 10 and 25 bits/min.

2.7 Conclusion

The performance of a pattern recognition system depends mainly on the features. For the feature extractions study, the CWT is a feasible technique, with a visual feedback of ERP and ERO in time-frequency domains for further analysis. Despite the existence of many works using CWT [Lachaux et al., 2002] [Bostanov, 2004] [Sakkalis et al., 2006], there is many potential works for use of the WC. This work intends to review this powerful technique, and exploit it as a measure of distance between the target and non-target stimuli, with the visual feedback similar to the CWT technique.

Chapter 3

Methodology

3.1 Introduction

The classification framework developed in this study has five steps based on knowledge discovery in databases (KDD) processes, described on figure 3.1. The first step is the data cleaning process. This process contemplates exclusion of signal discontinuities and its division on blocks. The subsequent step analyzes the blocks of trials using the CWT and WC statistical process. The objective of this analysis is to identify significant patterns that show dissimilarities, with higher than 95% of confidence level. On the third step, these patterns are represented by the scale-averaged wavelet power, which extracts the frequency features in a time vector. On step four, this vector is down-sampled to reduce its dimensionality, and normalized between 0 and 1 using all samples in the dataset. The fifth step uses the pre-processed vectors for cross-validation training of a Naïve Bayes Classifier (NBC) classification algorithm. The outcome of this step is the performance measurements that might change a specific preceding step or restart the entire process.

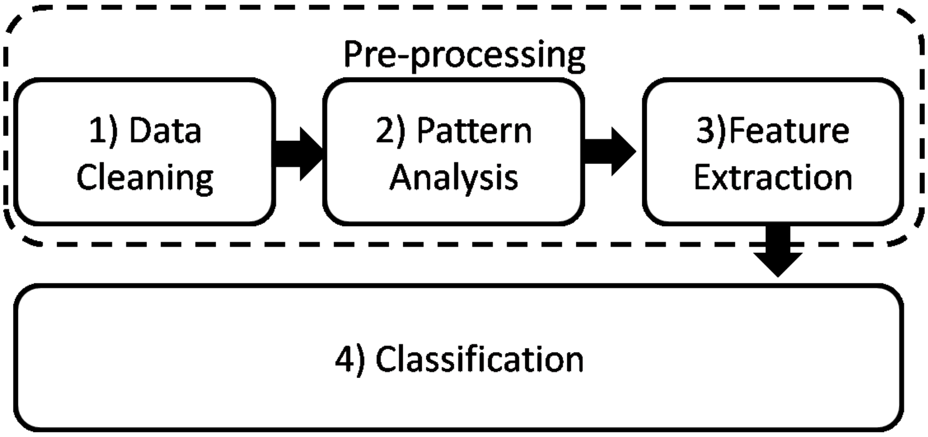

Figure 3.1: An overview of the framework purposed.

3.2 Signal Dataset

The signals used in this work were acquired, digitalized and make available by Hoffmann et al (2008) in École Polytechnique Fédérale de Lausanne (EPFL) [Hoffmann et al., 2008]. The dataset contains data from four disabled and four able-bodied subjects. These disabled subjects are all wheelchair-bounded; however they have different communication and limb muscle control abilities as described by them.

Each one of the eight subjects of the dataset was instructed to face a laptop screen, with six images as shown in fig. 3.2. The images exemplify an application scenario, which the user could control other devices like a television or a radio using the BCI. To evoking the P300 response each image flashes in a random sequence. Each one has four sessions with six runs (sequence of flashes). The first flash comes 400 ms after the beginning of the EEG recording. The image lights for 100 ms and during the following 300 ms none of the images is lighted. The stimulus flashes on a random sequence divided in blocks of 2 seconds. The stimuli are spaced by 400 ms from each other, the maximum time that a stimulus repeats is 4.400 ms, and the minimum is 400 ms. Each random sequence of stimuli is called a block. Fig. 3.3 shows these blocks with the six stimuli represented by each level 1 to 6. The non target stimulus is shaded on dark gray bars and the target are the white bars. The first stimulus begins at 400 ms, or at sample 820 with a 2048 Hz sample rate. The last stimulus finishes around 60 s. Each run contains an average of 150 stimuli, with 25 target stimuli.

Figure 3.2: The six images flashed used for evoking the P300. Source: [Hoffmann et al., 2008].

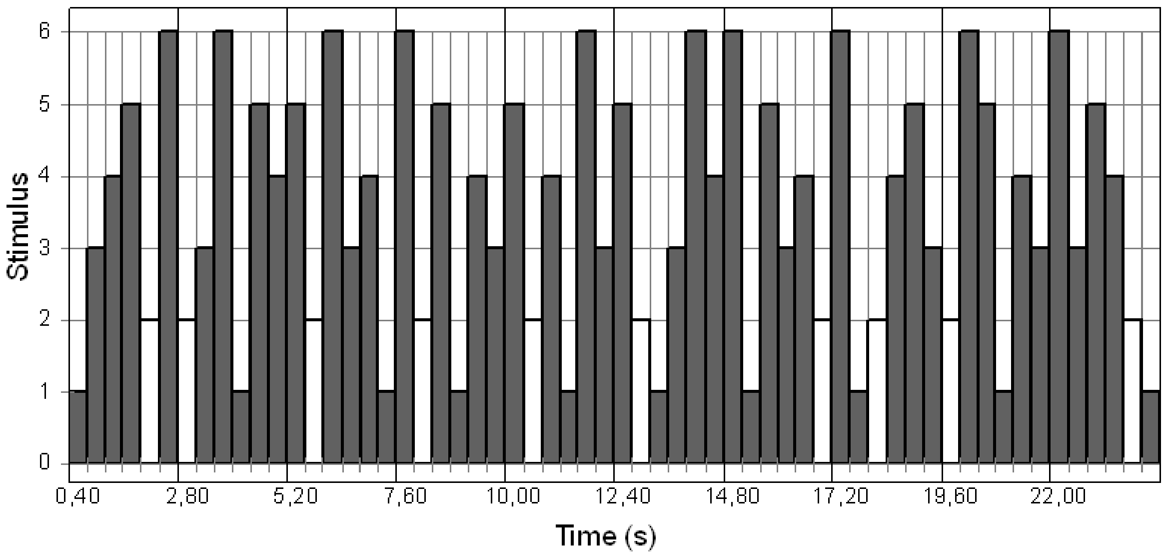

Figure 3.3: The sequence of stimuli divided in blocks.

The EEG used was recorded at 2048 Hz sampling rate from 32 electrodes placed at the standard positions of the 10-20 international system (as shown on figure 2.4). These electrodes were connected to a Biosemi Active Two® device, which amplify and digitalize the EEG signals.

The first step to analyze the signal is to review and to clean the signal from zeros and other external artifacts; on figure 3.4 the channels Pz, Oz, Fz and Cz exemplifies these artifacts showing a single recording session. Theses raw signal, as presented on figure 3.4-A, contain outliers, and this slice of signal must be excluded. In this particular example an outlier is presented at the end of the session, therefore the slice containing the outlier should be expelled, and the rest of the session is not affected. However, it is important to review each session for other outliers, such as presented on figure 2.5. The output of this process is exemplified on figure 3.4-B. The next step is to use the average signal form the two mastoid electrodes and reference all other channels; the following figure 3.4-C demonstrates the result of this referencing process, or also called by referential montage.

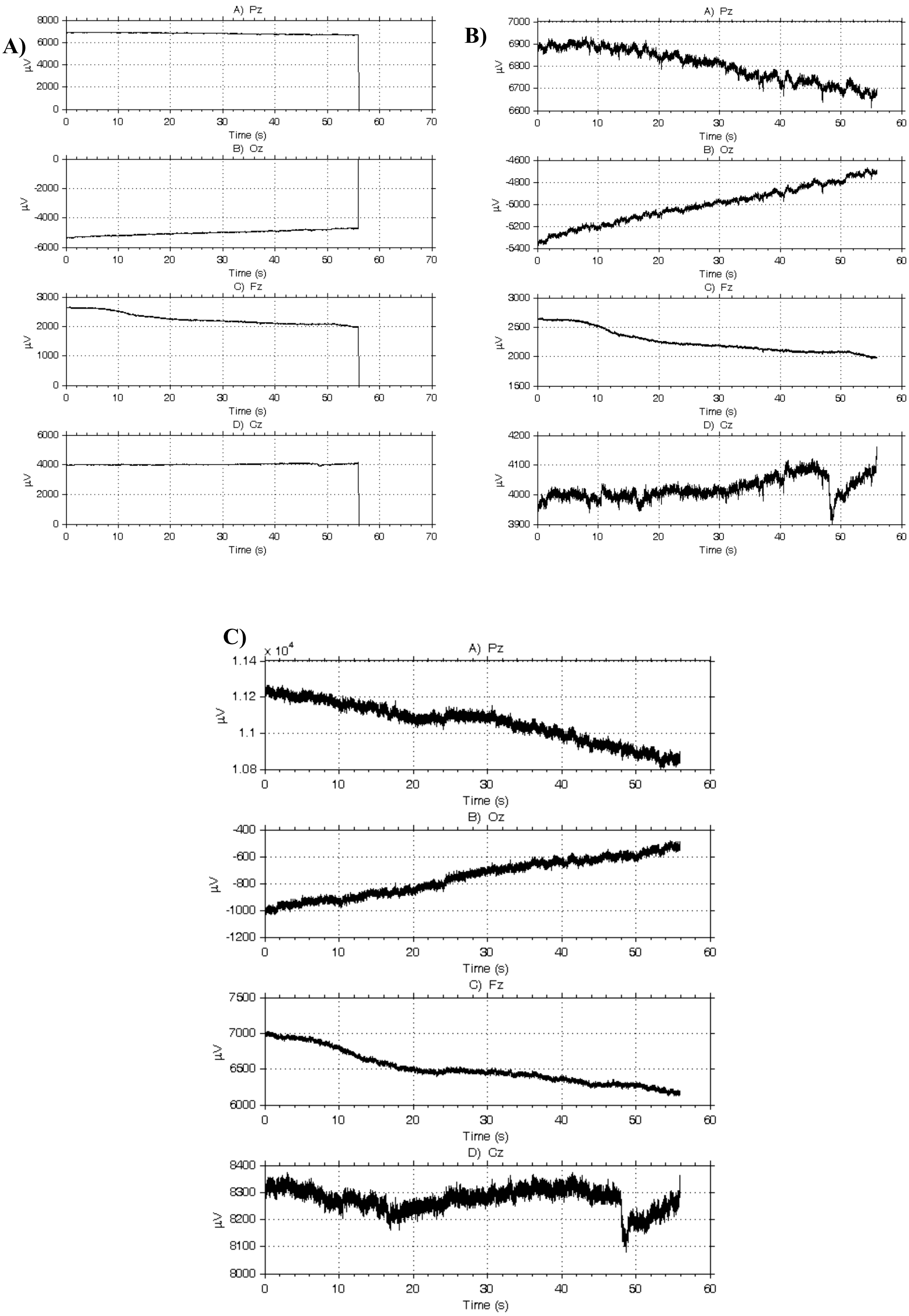

Figure 3.4: An EEG signal recording session of an locked-in subject during the three pre-processing step: A) a raw EEG of the four electrodes: Pz, Oz, Fz and Cz.; B) a raw EEG without outliers; and C) the referenced EEG.

3.3 Finite Impulse Response Filter

The filter used is a Finite Impulse Response Filter (FIR) with the equiripple method, a high-order filter with a linear phase and stable. This filter is close to the ideal with about 10dB/Hz slope in the transition bands, which frequency response is finite and rectangular. The Butterworth Filter also used is an infinite impulse response (IIR), in contrast to the FIR filter all poles are not located at the origin, and is therefore not always stable. Nonetheless, the IIR filters are preferred over the FIR filter, because the IIR filters could achieve sometimes a sharper transition region than the FIR filter of the same order. The magnitude and phase of each FIR filter built is presented on figure 3.4 and 3.5.

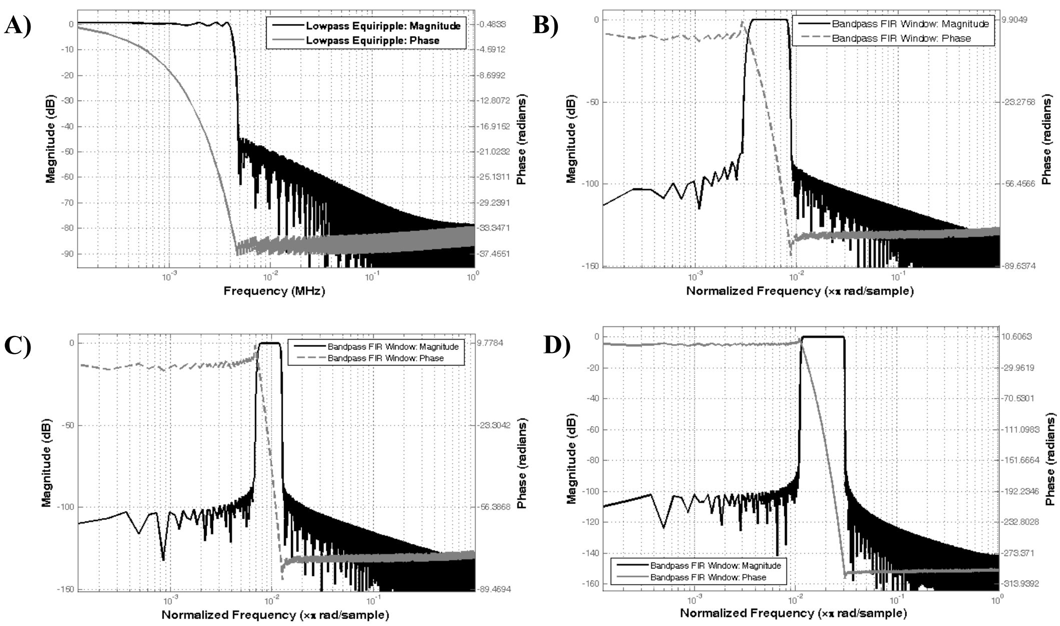

Figure 3.5: The magnitude and phase of each FIR filter: A) delta (0-4 Hz); B) theta (4-8 Hz); C) alpha (8-12 Hz); D) beta (12-30 Hz).

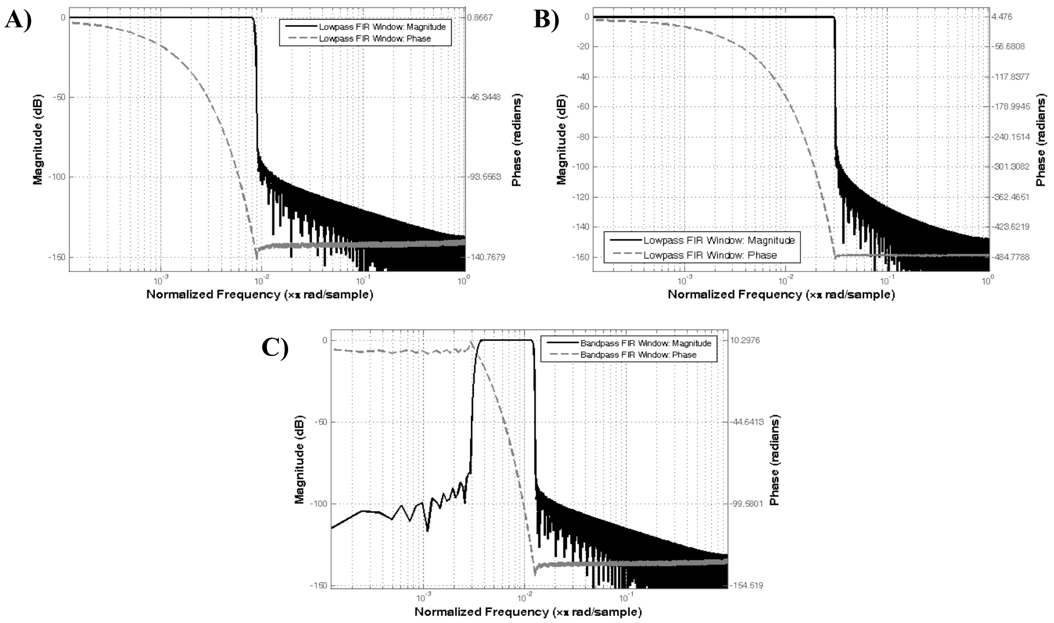

Figure 3.6: The magnitude and phase of each FIR filter: A) delta and theta band (0-8 Hz); B) delta to beta band (0-30 Hz); C) theta and alpha band of 4-12 Hz.

3.4 Continuous Wavelet Transformation

Each signal block is analyzed using a CWT, represented by $W_n(s)$ as defined in Eq. (3.1). The CWT is a convolution of x_n with a scaled and translated version of a wavelet function ψ, defined in the next section.

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'} \psi^* \left[\frac{(n'-n)\delta t}{s} \right] \tag{3.1}$$

The (*) indicates the complex conjugated of ψ, and s is the wavelet scale [Torrence and Compo, 1998]. Here, x_n represents a time series spacing by δt and the vector $n=0,\ldots,N-1$, and N is the number of points in the time series. The variation of the wavelet scale s and the translation of this function along the time generate the CWT. It can be constructed showing both the amplitude of any feature versus the scale and how this amplitude varies with time.

3.5 Morlet Wavelet Function

In order to apply the CWT technique the wavelet function is an important choice. It could be orthogonal or non-orthogonal, based on $\mathbb{C}$ or $\mathbb{R}$ domain, and many other fundamental requirements depending on the kind of features one wants to extract from the signal. To apply an acceptable function one must look at its reproducing kernel, which characterizes its space, scale and angular selectivity. This work chooses a complex-valued wavelet Morlet function, the most commonly used, indicated in Eq. (3.2).

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \tag{3.2}$$

, where $\psi(t)$ is the wavelet function that depends on a non-dimensional time parameter t, and i denotes the imaginary unit, $(-1)^{1/2}$. This wavelet function forms two exponential functions modulating a Gaussian envelope of unit width, where the parameter ω_0 is the non-dimensional frequency parameter, here taken to be 6 to satisfy the admissibility condition and having zero average [Farge, 1992].

In spite of that, the method presented is generally applicable to other wavelet functions, for example the Mexican hat. By using the Morlet instead of the Mexican hat, the wavelet transformation can extract features that are better located in the frequency domain, e.g. phase-locked ("evoked") gamma oscillations [Bostanov, 2004].

3.6 Cone of Influence

Fourier Transformations does not consider the edges of the time series, since its method assumes that the time series is cyclic. Nonetheless, the EEG signals are considered in this work a non-cyclic time series, and the edges will affect the time series analysis. The effect of these edges in CWT is called cone of influence (COI), and is composed by the two edges effects, each one forms a cone of influence through the scale. Exemplifying, for higher scale of periods (lower frequencies) fewer is the reliable results of the analysis, the decrease of this effects goes until a point where the beginning COI cross the end COI. These effects are illustrated on figure 3.6, that show a target time window from -0.2 seconds to 0.2 seconds, painted on gray. To get reliable results from the CWT analysis on this time window for the frequency of 2 Hz the data input time window must be higher than -0.884s to 0.884s. To analyze a 4 Hz frequency a lower data input time window is required, from -0.542s to 0.542s, illustrated by a dashed line on the figure 3.6.

Following the method of Meyer et al. (1993), the relationship between the equivalent Fourier period and the wavelet scale can be derived analytically for a particular wavelet function, by substituting a cosine wave of the know frequency into the wavelet transformation equation and computing the scale *s* [Meyers et al., 1993].

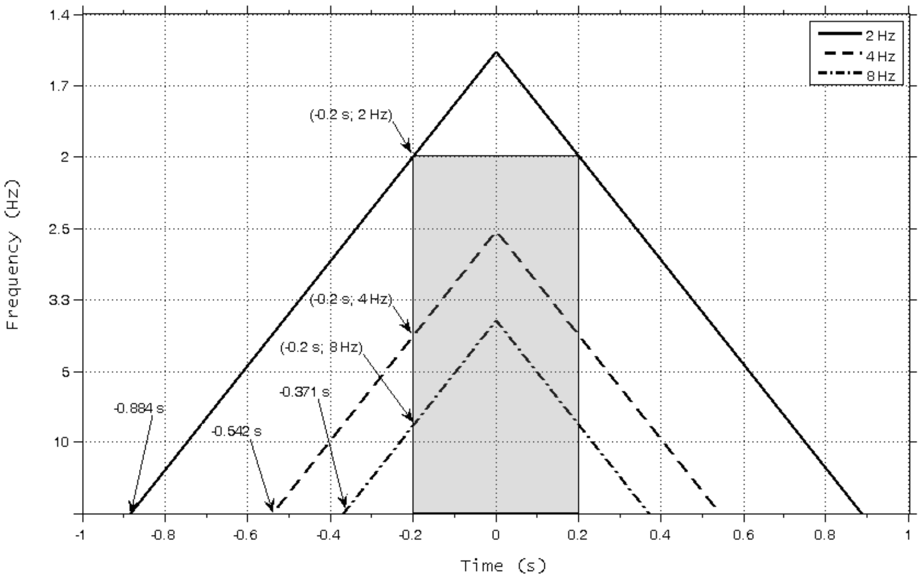

Figure 3.7: A correct position of the COI for a specific target time window in different target frequencies: 2 Hz, 4 Hz and 8 Hz.

3.7 Wavelet Power Spectrum

As the Morlet wavelet function is complex, so is the CWT, $W_n(s)$ defined on Eq. (3.1). Hence, the power spectrum defined as $|W_n(s)|^2$ is commonly used to represent this wavelet transformation. This power is used in WC and for representing a scale-averaged wavelet power, and is shown on figure 3.7. The outer elliptical region at the edges of the second graph with wide contour indicates the COI in which errors may be apparent due to the transformation of a finite-length series EEG signal. The Monte Carlo estimation of the significance level requires the order of 10.000 surrogated data set pairs. The thick contour designates the 5% significance. The captured rhythm signal could be visualized outside the COI, as showed on figure 3.7 A higher level of the power spectrum indicate a higher relationship level between the scaled wavelet and the time-frequency. For example, figure 3.7-A shows three graphs: the first is a sine signal of *t* with 2 Hz; the second is a wavelet spectrum power; and the third is the amplitude of the FT. The CWT indicates a higher level of spectrum power at 2 Hz, and the FT also identifies the sine frequency of 2 Hz. The same example is shown with other rhythms: the theta 6 Hz on figure 3.7-B; the alpha 10 Hz on 3.7-C; and the beta 16 H on 3.7-D.

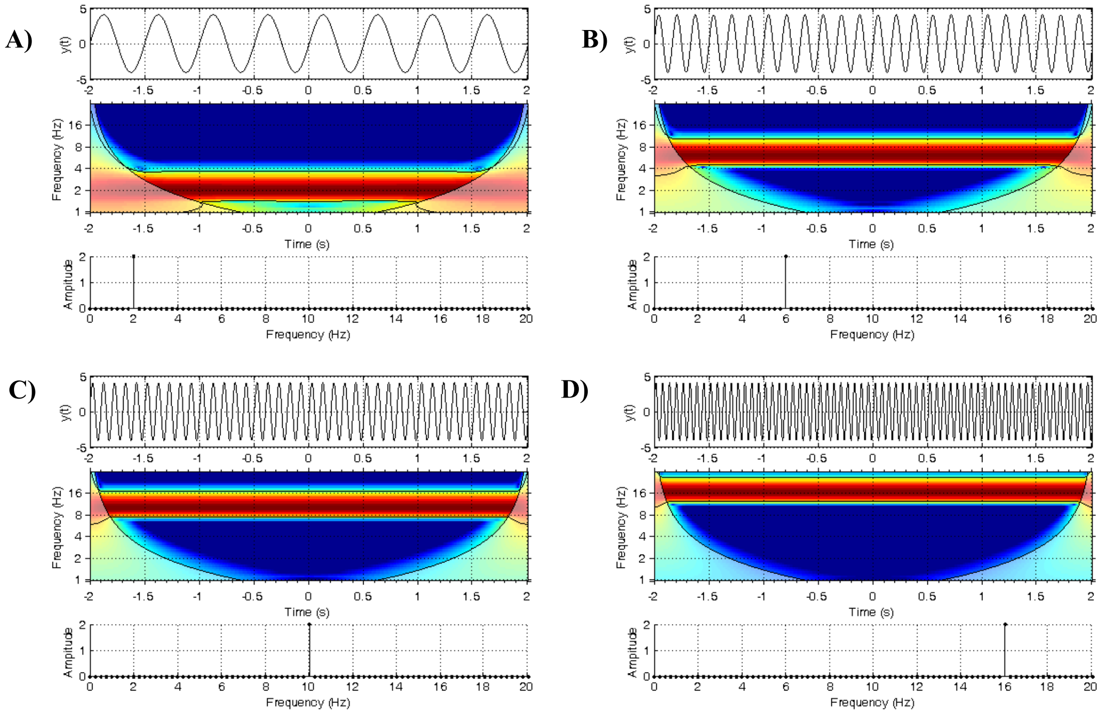

Figure 3.8: The sine signal of: A – delta (2 Hz); B – theta(6 Hz); C – alpha (10 Hz); and D – beta(16 Hz) rhythms; the CWT wavelet power spectrum of each signal; and the Fast Fourier Transformation Frequency of each signal.

Another example of the rhythm signal is showed on figure 3.8. The first example sum all four sine functions presented before, figure 3.8-A. And both CWT and Fourier Transformation (FT) presented the target frequencies as a result. On the next example each function is sequentially and exclusively presented, figure 3.8-B. The CWT shows each frequency in the time window that it occurs. The FT also shows each frequency, however the discontinuity of the signal produce a permanent noise in the signal. The last example shows the second example with a step signal, figure 3.8-C. The CWT presents higher levels of discontinuity, on the other hand the FT shows almost low frequencies of the discontinuities, and the targets sine functions are suppressed.

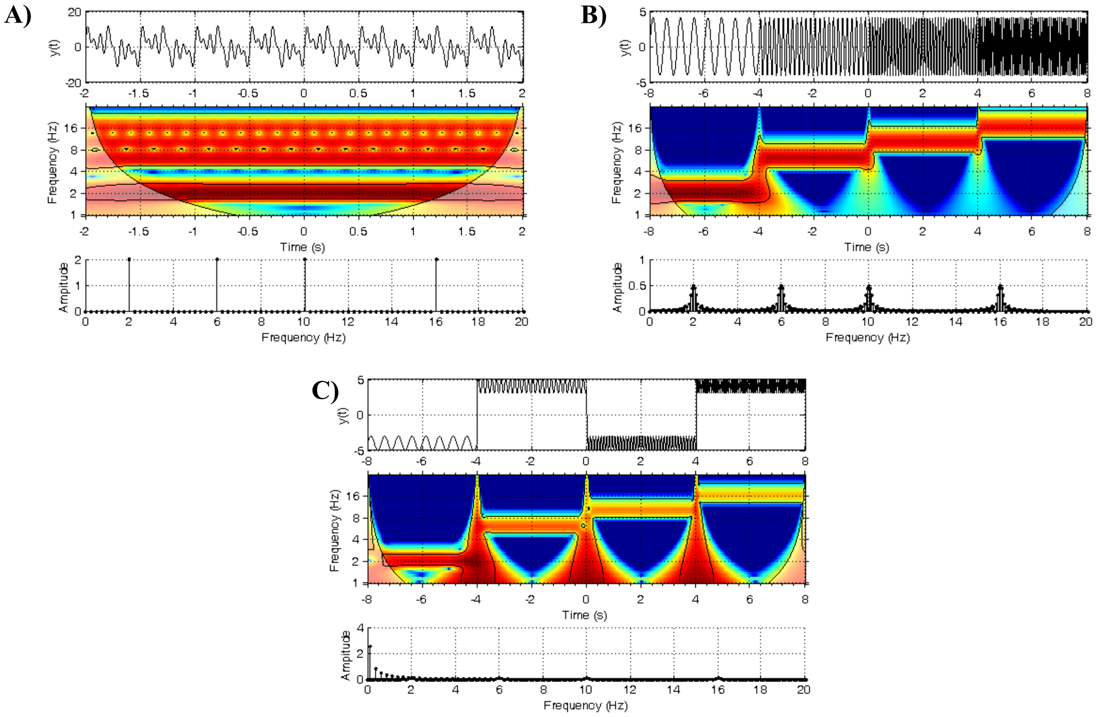

Figure 3.9: The sine signal of: delta (2 Hz); theta (6 Hz); alpha (10 Hz); and beta (16 Hz) are : A) summed together; B) sequentially and exclusively presented; and C) sequentially and exclusively presented with a step degree.

3.8 Wavelet Coherence

From the CWTs, average target W_n^X and non-target W_n^Y EEG response WC to analyze the similarities and synchronicity between the signals can be constructed. This could be illustrated as local correlation between both CWTs. This measurement is defined as the square of the cross-spectrum, defined on Eq. (3.3), and normalized by the individual power spectra. This gives a quantity between 0 and 1, and measures the cross-correlation from two time-series as a function of frequency, expressed on Eq. (3.4), where S is a smoothing operator. This operator smoothes the time and then smoothes the scale axis in both CWTs applied. The design of the smooth operator was based on Grinsted et al. [Grinsted et al., 2004].

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right).S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{3.3}$$

$$W_n^{XY}(s) = W_n^X(s)W_n^Y(s)^* \tag{3.4}$$

, where the W_n^{XY} is the cross-spectrum, between W_n^X and W_n^Y, the CWTs of target and non- target EEG response.

The statistical significance level of the wavelet coherence is estimated using Monte Carlo methods. A large ensemble of surrogate data set pairs was generated with the first order autoregressive coefficients (AR) for each calculated WC.

The phase difference is calculated using the complex phase angle. PCn(s) is the phase-coherence defined on Eq. (3.5), over regions with higher than 5% statistical significance that is outside the COI to quantify the phase relationship.

$$PC_n(s) = \tan^{-1} \frac{\Im\{W_n^{XY}(s)\}}{\Re\{W_n^{XY}(s)\}} \tag{3.5}$$

3.9 Scale-Averaged Wavelet Power

The scale-averaged wavelet power (SAWP) is used to represent a selected range of scales, here defined as non-dimensional frequencies *s*. This measurement is defined on Eq. (3.6).

$$\overline{W}_n^2 = \frac{\delta j \delta t}{C_\delta} \sum_{j=j_1}^{j_2} \frac{|W_n(s_j)|^2}{s_j} \tag{3.6}$$

, where W^2_n is the weighted sum of the wavelet power spectrum over scales s_1 to s_2, i.e. representing an average fluctuation power non-dimensional j_1 = 1Hz and j_2 = 4Hz of wavelet scale. The symbol δt is the time series spacing, the δj is the scale spacing, j is the scale series from j_1, $(j_1+\delta j), \ldots$ to j_2. The parameter C_δ is the reconstruction factor that Morlet function uses which is empirically set as equal to 0.776.

3.10 Naïve Bayes Classifier

The scale-averaged wavelet power measurement is a time-series extracted from the brains signal, organized in vectors which represent the user intention. The Naïve Bayes

Classifier (NBC) learns the user intentions from a set of training vectors. The NBC is characterized by two main advantages: the simplicity of its structure, and the speed of the learning algorithm it employs.

The probabilistic approaches make strong assumptions about how data is generated, and posit a probabilistic model about these assumptions. The Naïve Bayes classifier is the simplest of these models, and assumes all attributes of the example as independent of each other. While this assumption is intuitively false in most real-world tasks, the model often performs very well [Lin et al., 2008].

The NBC is a probabilistic classifier. This method simply classifies, for example, the vector $\boldsymbol{x}$ in the class c_k if it has the highest probability $P(c_k|x)$, where k is the number of classes. Following the Bayes theorem and the assumption of the independence between the features of the vector $\boldsymbol{x}$, this probability could be calculated using eq. 3.7.

$$P(c_k|x) = P(c_k) \times \frac{\prod_{j=1}^{d} P(x_j|c_k)}{P(x)} \tag{3.7}$$

The classifier searches for the maximum a posteriori probability hypothesis, on other words, the most probable hypothesis to fit the vector $\boldsymbol{x}$ at the class c_k.

Chapter 4

Experimental Results

4.1 Pattern Analysis

A vital feature of BCI system is the capability to distinct between the attended and ignored events with speed and accuracy. These characteristics differentiate artificial pattern recognition systems applied on BCI. This research develops a pattern recognition framework based on CWT and FIR filter feature extraction method. This framework intends to investigate the patterns recognized by those methods. Additionally, the framework review the EEG events with a pattern analysis method based on CWT.

An essential concern of pattern analysis is to comprehend, and understand the result patterns of the entire process. The CWT allows the illustration of patterns of each stimulus, and assists the staff and the user to comprehend the natural meaning of EEG patterns.

The recording session is divided in block as described on figure 3.1. Each block has five non target stimuli and one target stimuli. After the cleaning process, described on figure 3.1, the CWT is used to analyze some of the patterns in each EEG signal stimuli. In figure 4.1

one could visualize a common example of such analysis. The target and non-target of subject 2 are exemplified by the time-frequency wavelet spectrum. There, no significant region is presented by the frequency between 2-30 Hz, and the figure 4.1-A shows a slow increase on the waver spectrum power after the stimulus starts, approximately on 4 Hz. Figure 4.1-B shows a slow decrease of the wavelet power over that region. Another example of pattern is on frequencies higher than 8 Hz on figure 4.1. It shows a low average power on figure 4.1-A, in contrast to the higher average power on figure 4.1-B. Although these two patterns are not significant on any figure, the process of WC shows significant patterns most of it higher than 8 Hz, visualized on figure 4.3-A.

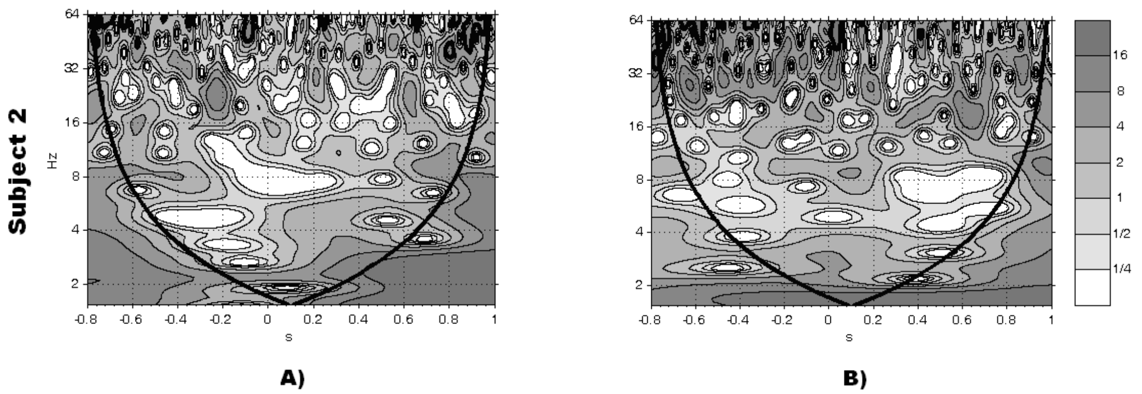

Figure 4.1: A CWT example from Subject 2 on Pz channel during: A) one target stimulus; B) and one non-target stimulus.

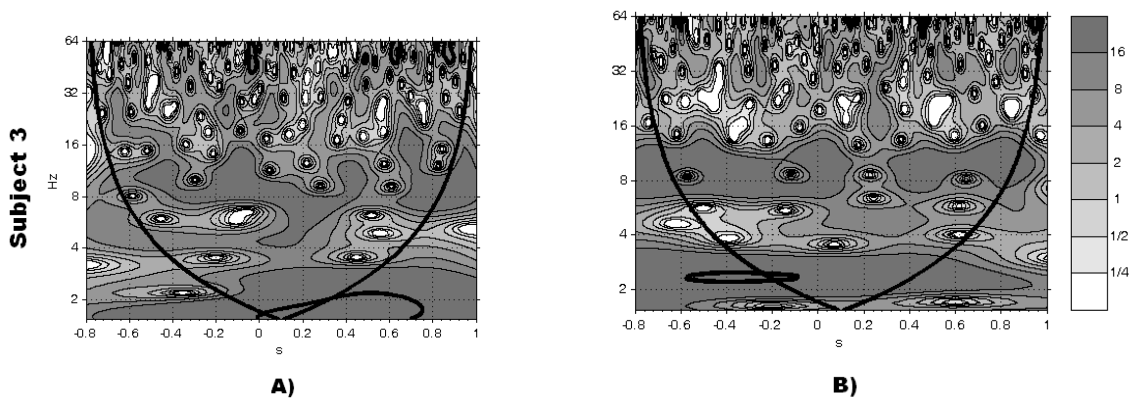

Figure 4.2: A CWT example from Subject 3 on Oz channel during: A) one target stimulus; B) and one non-target stimulus.

For each pair of target and non-target stimuli the wavelet coherence (WC) was calculated. Like on CWT, the outer elliptical region at the edges with wide contour indicates the Cone of Influence. The Monte Carlo estimation was also used for the significance level and it requires the order of 10.000 surrogated data set pairs. The thick contour designates the 5% significance level in figure 4.3. The number of scales per octave should be high enough to capture the rectangle shape of the scale smoothing operator while minimizing computing time. Empirical tests were run with 2, 5, 10, 15 and 20 scales per octave; the satisfactory computational costs obtained 5 scales per octave.

The WC analyzes the cross-correlation between the target stimulus and the non target stimulus at the same block. For Subject 2 the WC figure 4.3-A show some significant pattern around the stimulus start and with frequencies higher than 16 Hz. The coherence phase measurement shows an out-of-phase behavior. Subject 3 presented more significant cross-coherent signal patterns, visualized on figure 4.3-B. A pattern is observed on 4 Hz around the stimulus start, with an on-phase behavior.

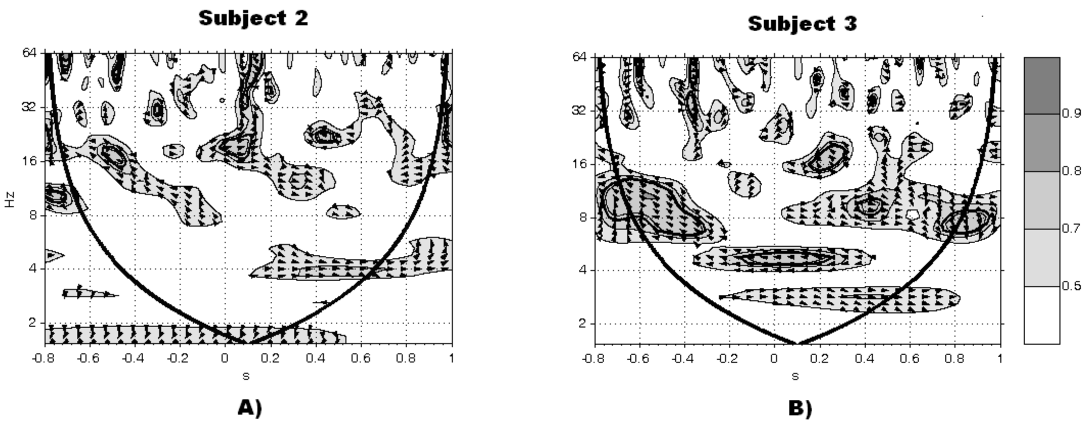

Figure 4.3: A WC example from A) Subject 2 on Pz channel between a target and non-target stimulus; B) Subject 3 on Oz channel between a target and non-target stimulus.

4.2 Feature Extraction methods

After the pattern analysis the features were extracted from the EEG trials. This procedure selects pre-defined frequency bands representations. The bands analyzed were: delta (2-4 Hz), theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz). Additionally, the oscillations of the delta and theta band (0-8 Hz), a delta to beta (0-30 Hz), and the band of 4-12 Hz applied by Hoffmann et al on a Butterworth filter [Hoffmann et al., 2008]. Those frequencies were used by three feature extraction methods: the filter, the CWT and the combination of the filter and the CWT. The first one uses a FIR filter process and also the Butterworth filter. On this experiment the CWT was not applied, and the FIR filter process is tested with each analyzed band, e.g. the filter selects a particular frequency band delta (2-4 Hz) setting the cutoff frequency to 2 and 4 Hz, shown on figure 4.2-A. Additionally, the data set was tested without the filter process, to mark a base line for both methods. The second set of experiments tests the performance of the CWT without the filter process. A scale-averaged wavelet power were uses the EEG trials to process selecting each frequency band from the CWT. And the third set of experiments combines the filter process first with the scale-averaged wavelet power. The filter selects a specific frequency band and the CWT is applied in this band also.

4.3 Classification

A BCI classifier should test mainly the precision and communication speed of the BCI system. This work uses a Naïve Bayes Classifier implemented by the software WEKA (Waikato Environment for Knowledge Analysis) to perform the classification. The class used applies a Naïve Bayes Updatable Classifier and the default precision is 1% for the current dataset; for further details of the algorithm consult [John and Langley, 1995]. The general performance was obtained through k-fold cross-validation using 10x10-folds method [Dietterich, 1997]. This technique divides the data randomly into ten parts, each part is held out in turn and the learning scheme is trained in the remaining nine parts. The procedure is repeated ten times and the average for the ten parts is calculated, for cross-validation training and validation procedure.

The decision made by the classifier is organized in a structure known as a confusion matrix or contingency table, shown on Table 4.1. The confusion matrix has four categories: True positives (TP), False positives (FP), True negatives (TN) and False negatives (FN). Given the confusion matrix, we are able to define each metric: the precision on eq. 4.1, recall on eq. 4.2, sensitivity on eq. 4.3, specificity on eq. 4.4 and accuracy on eq. 4.5.

Table 4.1: Confusion Matrix.

	Actual class	
	Target	***Non-target***
Predicted Target	***TP***	***FP***
Predicted Non-target	***FN***	***TN***

Precision:	***TP / (TP + FP)***	(4.1)
Recall(Sensitivity):	***TP / (TP + FN)***	(4.2)
Specificity:	***TN / (TN + FP)***	(4.3)
Accuracy:	***(TP + TN) / (TP + TN + FP + FN)***	(4.4)

Each run contains 150 stimuli, with 25 target stimuli and 125 non target stimuli. This unbalanced proportion of samples in class targets with 16% and non target with 83% of stimulus difficult the training process and could generate a tendentious response of the classification process. If the classifier responds always a non target class, its accuracy, defined by eq. 4.4 will be 83%. An acceptable solution should analyze all stimuli as a different class, avoiding tendentious responses. This work considers only the accuracy of the target class, and the averaged accuracy of all non target classes. This decision not only avoids the tendentious response to the system, but also allows reviewing the system performance with reliable metrics. So the accuracy baseline for all classifier is 50%, any lower performance is invalid.

The speed of communication is an important characteristic of a BCI system. This feature depends on interstimulus interval, the number of different stimuli, the classification accuracy, and the control flow algorithm. The bit rate is a theoretical measurement that simulates all these factors as a performance metric for the speed of communication, and it is used to compare BCI systems. The bit rate b in bits/min can be computed according to the following eq. 4.5 [Wolpaw et al., 2000]

$$b(N,p,t)=\left(\log_2(N)+p\log_2(p)+(1-p)\log_2\left(\frac{1-p}{N-1}\right)\right)\frac{60}{t} \tag{4.5}$$

,where the variable N denotes the number of different commands a user can send, which is six for this approach. Furthermore, p denotes the probability that a command is correctly recognized by the system. The t is the time in seconds that is needed to send one command. Th is work studies each stimulus individually, the stimuli time window is one second, and it begins 0.2 seconds before its occurrence.

4.4 Experiments

The eight subjects of the dataset were submitted by fourteen tests, which return the accuracy, the bitrate, the specificity and sensitivity of the Naïve Bayes Classifier. The performance of the BCI systems tests three different feature extraction methods: without filtering; with FIR filter and Butterworth filter; and with the CWT with scale-averaged wavelet power. These methods are applied on seven different frequency bands: 2-4 Hz; 4-8 Hz; 8-12 Hz; 12-30 Hz; 2-8 Hz; 2-30 Hz; and 4-12 Hz.

The first experiment is to obtain the classification performance of the FIR filter process and also the Butterworth filter. Additionally, the data set was tested without the filter process. The EEG filtered signal measurement is used as an input signal for the NBC algorithm directly. As a result, the data set is optimally classified into two classes, targets and non targets following the validation process, and an average accuracy metric is then calculated; the results can be visualized on fig. 4.4.

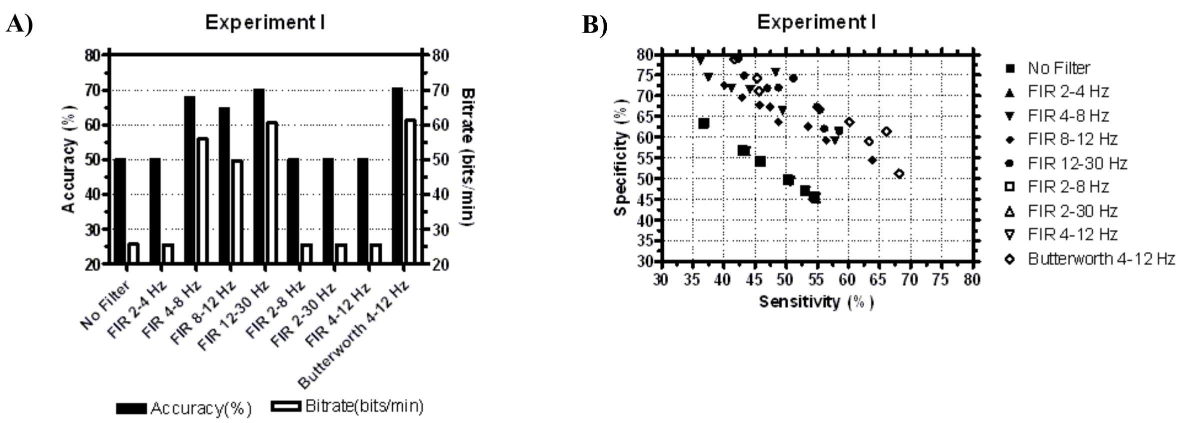

Figure 4.4: The results of Experiment I represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

The second set of experiments tests the performance of the CWT without the filter process. The wavelet transformation uses the scale-average wavelet power measurement to select each analyzed frequency band setting the parameters s1 and s2 on Eq 3.6. Following, the SAWP measurement is applied on NBC algorithm, and the results of this classification are calculated, as showed on fig. 4.5.

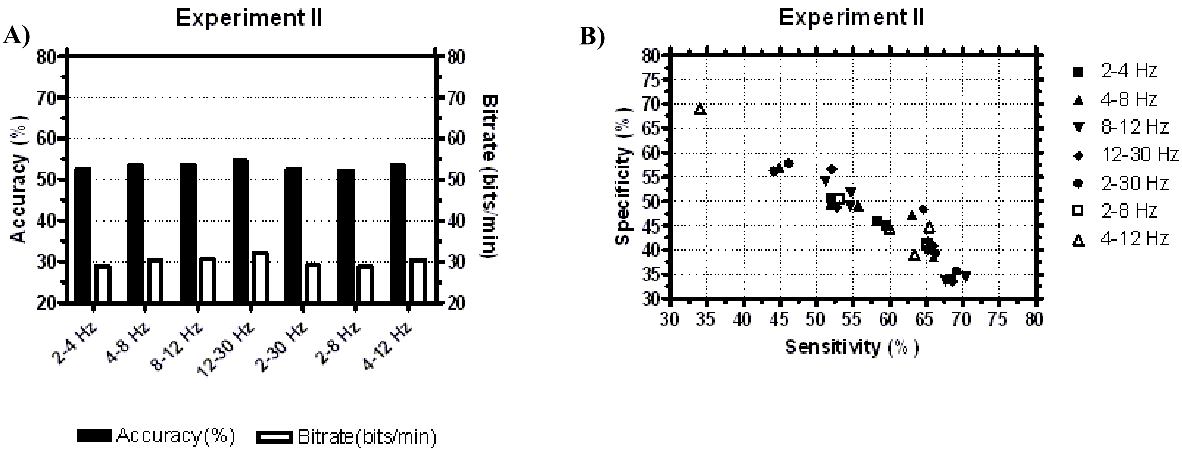

Figure 4.5: The results of Experiment II represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

The third set of experiments combines the target filter process with the CWT. The filter selects a specific frequency band and the CWT is applied also in this band, generating a vector with the SAWP applied on the NBC, the results are presented on fig. 4.6.

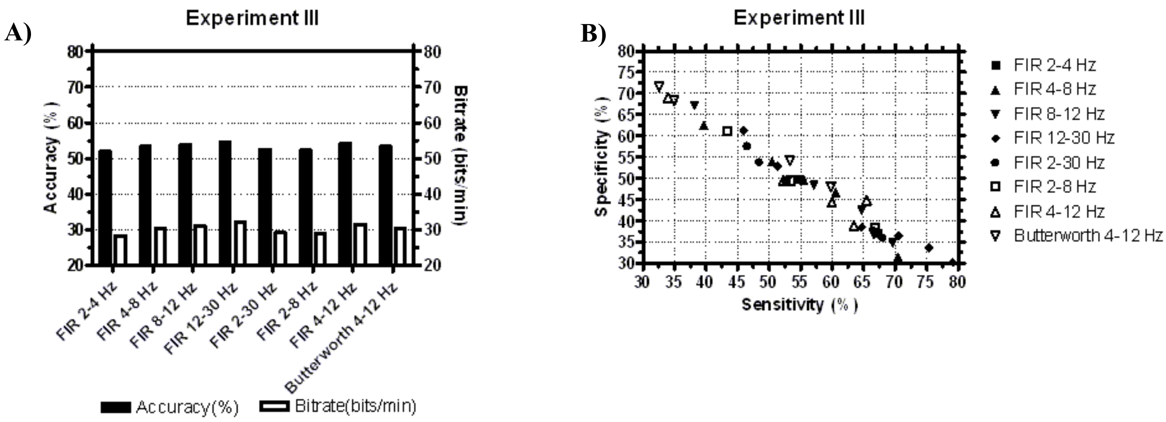

Figure 4.6: The results of Experiment III represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

The next experiments describe the use of the FIR filter or the Butterworth filter initially, and the CWT method is also applied. Nonetheless, the CWT method is applied on a set of possible frequency bands inside the initial filtered frequency band. The result of this method is shown on: FIR 2-8 Hz (fig. 4.7); FIR 2-30 Hz (fig. 4.8); FIR 4-12 Hz (fig. 4.9); and Butterworth 4-12 Hz (fig. 4.10).

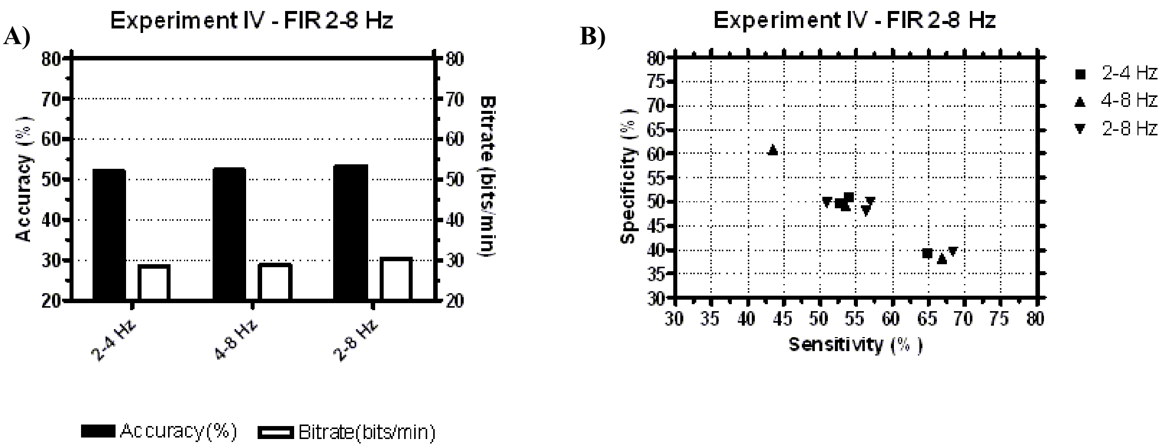

Figure 4.7: The results of Experiment IV represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

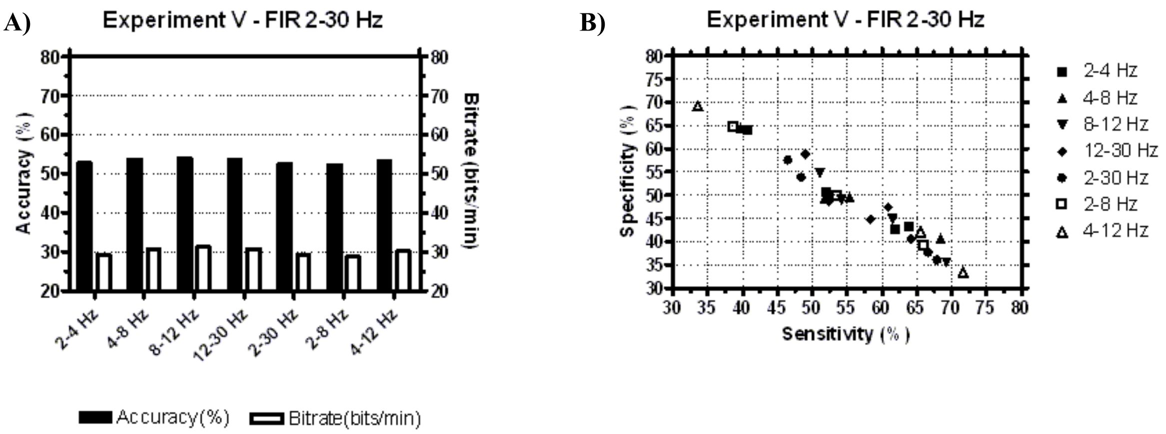

Figure 4.8: The results of Experiment V represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

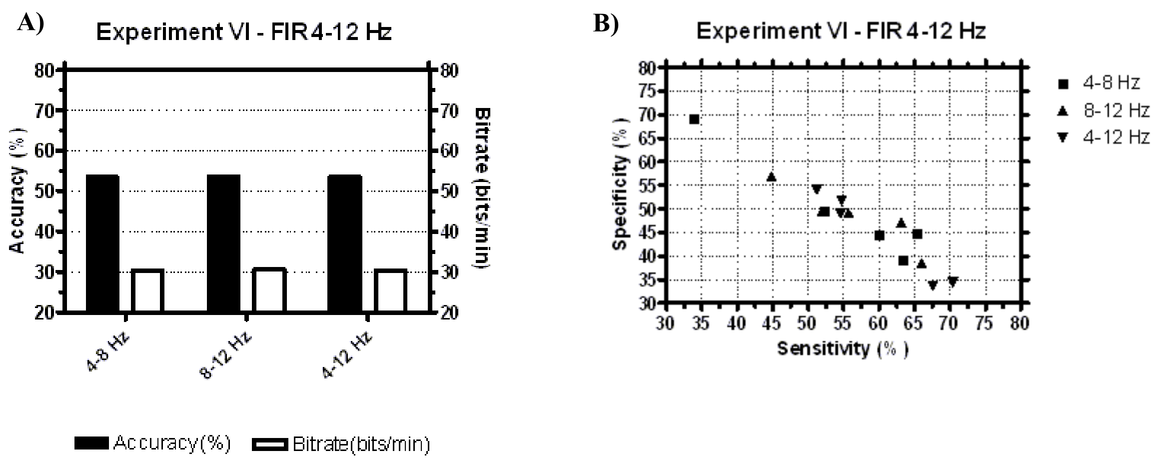

Figure 4.9: The results of Experiment VI represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

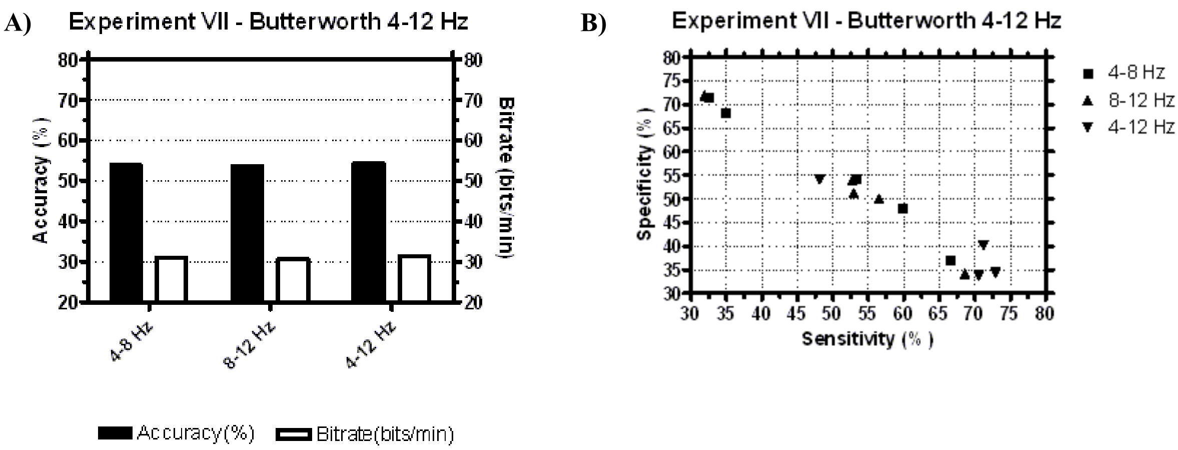

Figure 4.10: The results of Experiment VII represented by A) Accuracy and Bitrate; and B) Specificity and Sensitivity.

The base line of 50% of accuracy shown on figure 4.4 without the filter process was not achieved by other experiments. Although the results didn’t achieve a expressive accuracy increase with the CWT, or with both filter process and the CWT, the results present a slightly increase of 5% for the specific frequencies of 12-30 Hz and 4-12 Hz, as suggested by the WC analysis on figure 4.3, with significant signal exemplified by subjects 2 and 3 around 4 Hz and 16 Hz.

Chapter 5

Conclusion

5.1 Summary of results

The results on figure 4.4 could be described as two groups. The first group is represented by all tests which performed under 55% of accuracy and under 25 bits/min, which includes the tests without filter, and with the filter FIR 2-4 Hz, FIR 2-8 Hz, FIR 2-30 Hz, and FIR 4-12 Hz. Those methods do not present reliable results, due a low accuracy result.

The second group is composed by the tests which achieve a higher accuracy and bit rate performance, such as FIR 4-8 Hz, FIR 8-12 Hz, FIR 12-30 Hz and Butterworth 4-12 Hz. The highest accuracy was 70,34%, and the highest bit rate was 61,15 bits/min, both from the Butterworth filter. The FIR 12-30 Hz achieves also a high accuracy of 70,04% and bit rate 60,51 bit/min. Furthermore, the average specificity of this test (68,74%) was higher than the Butterworth test (67,38%). This difference is significant because the Butterworth has higher false positive proportion, it means that this method have a tendency to classify more non target stimulus as being a target stimulus than FIR 12-30 Hz. And the difference of specificity between these tests is higher than the difference between their accuracies. The FIR 12-30 Hz is reasonable method to obtain more reliable results, then the Butterworth filter.

The experiment II, III, IV, V and VI present a lower accuracy compared with experiment I. The accuracy results for these experiments did not achieve a significant performance. The bitrate is approximately 29 bits/min and the averaged accuracy is approximately 52%. Although they had a low accuracy, their bit rate performance is equal to the state-of-art (Hoffmann et al achieved 29 bits/min) [Hoffmann et al., 2008]. Wolpaw et al assumed that the user communicates an infinite amount of data, and the data is encoded. The BCI has a limited amount of data, and this interface does not apply any encode process in this case. Therefore, on this work a lower accuracy performance doesn't represent a system that is performing worst or better then the state-of-art.

The increase on the bit rate measurement occurs due the reduction of the time window analyzed, with only one second of length. This time window enables 60 characters per minute. A subject without disabilities types on a computer an average of 95 characters per minute, while composing a text [Galitz, 2007]. Therefore, in this case an increase in communication speed (characters per minute) causes a decrease in the accuracy. The chosen solution of FIR 12-30 Hz could represent a reliable solution with an averaged accuracy of 70,04% and 60,51 bit/min, enabling a communication of 60 characters per minute.

5.2 Discussion

The main purpose of this work was to develop an exploratory approach for EEG signal, in which the patterns could be studied in the time-frequency plane. This innovative characteristic of the technique justifies the feasibility of the proposed approach on other data mining applications. This approach allows the study of not only the most prominent pattern, and at the same time it allows the visualization and classification of other time-frequency windows. Furthermore, it can also open new physiologic studies on this field and on non stationary time series analysis.

The algorithmic approach sketches the idea of using statistically-based feature vectors in the time-scale CWT domain in order to select the most relevant time-frequency segments able to show the most prominent task changes out of the background signal. Results suggest that the proposed methodology is also able to identify regions of the WC spectrum during the specified task. Moreover, in the identified regions, patterns could be used by a classification algorithm, as the NBC, to translate the EEG-signal to control commands. Further studies are necessary to determine the extent and possible causes of the patterns recognized.

5.3 Further Works

Brain-computer interface (BCI) provides a nonmuscular communication channel. This channel could be used on several application, such as assisting people with severe motor disabilities [Wolpaw et al., 2003], supporting biofeed-back in people suffering epilepsy [Strehl et al., 2006b], stoke [Buch et al., 2008], attention deficit hyperactive disorder [Strehl et al., 2006a], diagnostic of Alzheimer disease [Polikar et al., 2008], or even controlling computer games [Mason et al., 2004]. While researchers have demonstrated this technology in the laboratory, it is not ready for use in real world situations. The BCI robustness of the technology requires more improvements to be considered a practical and reliable technology. Further works should consider other filter techniques, with a deeper study on 12-30 Hz frequency band.

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