

**HISTOGRAM OF GRADIENT ORIENTATIONS OF SIGNAL PLOTS
FOR BRAIN COMPUTER INTERFACES**

por
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Abstract

Brain Computer Interface (BCI) or Brain Machine Interfaces (BMI), has proved the feasibility of a distinct non-biological communication channel to transmit information from the Central Nervous System (CNS) to a computer device. Promising success has been achieved with invasive BCI, though biocompatibilities issues and the complexity and risks of surgical procedures are the main drive to enhance current non-invasive technologies.

Electroencephalography (EEG) is the most widespread method to gather information from the CNS in a non-invasive way. Clinical EEG has traditionally focused on temporal waveforms, but signal analysis methods which follow this path has been overshadow in BCI research.

This thesis propose a method and framework to analyze the waveform, the shape of the EEG signal, using the histogram of gradient orientations, a fruitful technique from Computer Vision which is used to characterize image local features. Inspiration comes from what traditionally electroencephalographers have been doing for almost a century: visually inspecting raw EEG signal plots.

The validity of the method is verified by identifying and detecting Visual Occipital Alpha Waves and Motor Imagery Rolandic Mu rhythms. It is also applied on P300 ERP detection and used to implement a P300-Based Visual Speller application. Experimental protocols to produce these cognitive patterns were designed and own datasets produced and published using both commercial-grade and research-grade EEG devices. Obtained results on public and own datasets are outlined and described, and comparisons performed against similar procedures.

The benefits of the approach presented here are twofold, (1) it has a universal applicability because the same basic methodology can be applied to detect different patterns in EEG signals with applications to BCI and (2) it has the potential to foster close collaboration with physicians and electroencephalograph technicians because this direction of work follows the established procedure of the clinical EEG community of analyzing waveforms by their shapes.

Abstract

Brain Computer Interface (BCI) or Brain Machine Interfaces (BMI), has proved the feasibility of a distinct non-biological communication channel to transmit information from the Central Nervous System (CNS) to a computer device. Promising success has been achieved with invasive BCI, though biocompatibilities issues and the complexity and risks of surgical procedures are the main drive to enhance current non-invasive technologies.

Electroencephalography (EEG) is the most widespread method to gather information from the CNS in a non-invasive way. Clinical EEG has traditionally focused on temporal waveforms, but signal analysis methods which follow this path has been overshadow in BCI research.

This thesis propose a method and framework to analyze the waveform, the shape of the EEG signal, using the histogram of gradient orientations, a fruitful technique from Computer Vision which is used to characterize image local features. Inspiration comes from what traditionally electroencephalographers have been doing for almost a century: visually inspecting raw EEG signal plots.

This technique can be outlined in five steps, (1) signal preprocessing, (2) signal segmentation, (3) transformation on a channel by channel basis of each signal segment into a binary image of a signal plot, (4) assignment of keypoint location on a position over the newly created image depending on the physiological phenomena under study and finally (5) the calculation of the histogram of gradient orientations using finite differences from the image around this keypoint. This method generates a feature, a normalized 128-dimension descriptor. This feature is used to compare the signal segments that were used to generate them, hence to analyze the underlying cognitive phenomena.

The validity of the method was verified by studying three cognitive patterns. First, Visual Occipital Alpha Waves are analyzed. An experimental protocol is designed and a dataset is produced using a commercial-grade EEG device. Additionally, the ability of the method to capture oscillatory processes is verified by analyzing a public dataset. Moreover, this methodology is extended to study a related oscillatory process: Motor Imagery Rolandic Mu rhythms. The performance of the method to discriminate right vs left

motor imagery against a public dataset of healthy subjects is verified. Results are informed and reported. Finally, the method is modified to capture transient events, particularly the P300 Event Related Potential. A minute description on how to extract the ERP from the EEG segment is offered, and a detailed description of how to implement a P300-Based BCI Speller application is outlined. Its performance is verified by processing a public dataset of ALS patients and contrasted against an own dataset produced in house replicating the same experimental conditions.

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Resumen

Lists of Publications

The following publications are the basis of this thesis

- Ramele, R., A.J.Villar, and J.M.Santos."A Brain Computer Interface Classification Method Based on SIFT Descriptors." VI Latin American Congress on Biomedical Engineering CLAIB 2014, Paraná, Argentina 29,30,31 October 2014. Springer International Publishing, 2015.
- Ramele, R., A. J. Villar, and J. M. Santos. "A Brain Computer Interface Classification Method Based on Signal Plots." 4th Winter Conference on Brain Computer Interfaces, Yongpyong, Korea, February 2015. IEEE Signal and Processing, 2016.

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List of Acronyms

The following abbreviations are used in this thesis:

EEG: electroencephalography

BCI: Brain Computer Interfaces

SNR: Signal to Noise Ratio

CNS: Central Nervous System

ALS: Amyotrophic Lateral Sclerosis

ERP: Event-Related Potential

P300: Positive deflection of an Event-Related Potential which occurs 300 ms after onset of stimulus

ITR: Information Transfer Rate

BTR: Bit Transfer Rate

SIFT: Scale Invariant Feature Transform

HOG: Histogram Of Gradients

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Introduction

The brain is a machine with the sole purpose to respond appropriately to external and internal events, and to spread its own presence into the environment where it belongs¹. Hence, the brain needs to communicate and it posses mainly two natural ways to do it: hormonal or neuromuscular. When those natural channels are interrupted, they are not available or when it needs to increase or enhance the communication alternatives, a new artificial communication channel which is not based on them, is needed. It is based, instead, on a new technology feat that decode the information from the CNS and transmit it directly to a computer or machine.

Brain Computer Interface, BCI, is a system that measures brainwaves and converts them into artificial output that replaces, restores, enhances, supplements or improves natural CNS output and changes the ongoing interactions between the Central Nervous System (CNS) and its external or internal environment [88]. Brain Machine Interface (BMI) generally refers to invasive devices and Brain Neural Computer Interfaces (BNCI) may refer to devices that do not exclusively use information from the CNS, they also may use any kind of biological signal that can be harnessed with the purpose of volitionally transmit information. Above all, BCIs are communication devices.

There are five motives behind BCI: the **first** is the Aging of Societies: estimated for 2025, 800 millions people will be over 65 years old, and 2/3 of them on developing countries [43]. This may lead to an increased tendency to develop diseases that affect motor pathways and require some form of assistance from technology. The **second** reason is the digital world that calls for more methods of interactions. This digital society demands more mechanisms to interpret our surrounding world and to translate our intentions through digital gadgets. Additionally, the advancement of wearable devices and the proliferation of smart machines is also pushing the frontiers to go deeper into the body and find there useful information. The **third** motive is the impulse of Neuroscience Research and the advances that this discipline is having worldwide. The **fourth** reason is the potentialities of BCI as a clinical tool which can help to diagnose diseases, as aid in the field of neurorehabilitation, or to

¹The sensorimotor Hypothesis [91, 88] and The Extended Mind Thesis [18]

provide neurofeedback. The **fifth**, final and most important motive, the reason behind Brain Computer Interfaces, is the still unfulfilled societal promise of social inclusion of people with disabilities. It is known that the ability to walk and live independently is a key indicator of psychological and physical health, and we have to do all we can to provide the technological tools to achieve this goal[?].

In line with the aforementioned motives, there are several applications currently under development for BCI. People affected by any kind of neurodegenerative diseases, particularly those affected by advanced stages of amyotrophic lateral sclerosis (ALS) with locked-in syndrome may find in BCIs the only remaining alternative to communicate. Other applications targeted for the general population include alertness monitoring, telepresence, gaming, education, art, human augmentation [?] biometric identification, virtual reality avatar, assistive robotics and education. Novel niches where this new communication channel can be useful are found routinely [?]. If you are a newcomer to this discipline a word of warning: there is still a long way ahead. This area advanced rapidly but the complexity of brain signals in all their forms is still a big problem to tackle.

Electroencephalography (EEG) is the most widespread device to capture electrical brain information in a non-invasive and portable way, and it is the most used device in BCI research and applications. The clinical and historical tactic to analyze EEG signals were based on detecting visual patterns out of the EEG trace or polygraph[28]: multichannel signals were extracted and continuously plotted over a piece of paper. Electroencephalographers or Electroencephalography technician have decoded and detected patterns along the signals by visually inspecting them [72]. Nowadays clinical EEG still remains a visually interpreted test [28].

In contrast, automatic processing, or quantitative EEG, was based first on analog electronic devices and later on computerized digital processing methods [35]. They implemented mathematically and algorithmically complex procedures to decode the information with good results [92]. The best materialization of the automatic processing of EEG signals rests precisely in the BCI discipline, where around 71.2% is based on noninvasive EEG [25].

Hence, the traditional approach was mainly overshadow in BCI research, and the waveform of the EEG was replaced by sound procedures that were difficult to link to existing clinical EEG knowledge.

On the other hand, the Histogram of Gradient Orientations is a method from Computer Vision useful to image recognition that aims to mimetically reproduce how the Visual Cortex

discriminate shapes.

This thesis tries to unravel the following question: is it possible to analyze and discriminate Electroencephalographic signals by automatic processing the shape of the waveforms using the Histogram of Gradient Orientations ?

To do that, I humbly ask the reader to join me in this brief journey: Chapter 1 gives details of what is Brain Computer Interfaces and the particularities of the first window of the electric mind: the EEG. It also covers the state of the art in the methods that explore the waveform automatically. The Chapter 2 provides an overview on the procedure to construct a plot representing the signal. Chapter 4 is the core of this thesis and describes the Histogram of Gradient Orientations and how it can be used to process one-dimensional signals. Next, results and experimental procedures are described for the experimented EEG signals and BCI paradigms: Alpha Waves are covered in Chapter 5 and Motor Imagery in Chapter 6. The P300 Wave is studied in Chapter 7. Future Work and Conclusions are addressed in A. Finally, appendixes provide extra additional information regarding the state-of-the-art of this discipline in Argentina, and also outlines particularities of the SIFT method and the theory behind the Histogram of Gradient Orientations of Signal Plots.

0.1 Significance

This thesis propose

- A procedure to construct analyzable 2D-images based on one-dimensional signals.
- A mapping procedure to link time-series characteristics based on feature of the 2D-image representation.
- A feature extraction method for EEG signals that can be used objectively to construct a representation of the waveform.
- A classification algorithm that can be used effectively with these features.

0.2 Summary

- What is this all about?: a method to analyze EEG signals based on extracting local feature from their 2D image representation.
- What you won't find in this thesis?: yet another description of BCI.

- What you will find in this thesis?: a point of view that emphasizes the importance of providing mechanisms that help to understand signals based on how they look like on plots.
- Does it work?: It works when the waveform contains the discriminative information. If a person is able to discriminate the signals, this method would also do that.
- Can I use it?: Yes you can. The software to use it is open-source and you can use out-of-the-box. It is particular useful when you need to have an explanation of the classification procedure.
- Why I do not use something else?: If you need to emphasize the shape of the waveform, this is what you are looking for.

Chapter 1

The Brain, The Computer and The Interface

Deus ex machina!

Aeschylus

With Vidal's work in 1970s, Brain-Computer Interfaces started as a technological amusement, and it steadily moved toward a mature and highly researched area of work. Outstanding success has been achieved with invasive BCI, i.e. with surgically implanted electrodes. Success stories have been made public like Braingate's implant on Jan Scheuermann, Cathy Hutchinson and Dennis Degray [59]. Other works include the total reproduction of arm movement [29], the restoration of reaching and grasping movements through a brain-controlled muscle stimulation device on a person with tetraplegia [3] and the remote control of a manipulator by a macaque using brainwave information [87] albeit of persistent biocompatibility issues and the pervasive complexity and risks of surgical procedures. One noteworthy aspect of this novel communication channel is the ability to transmit information from the Central Nervous System (CNS) to a computer device and from there use that information to control a wheelchair [14], as input to a speller application [26], in a Virtual Reality environment [46] or as aiding tool in a rehabilitation procedure [39]. Other novel applications include the real-time control of flight simulators [56] and the implementation of neuroadaptive interfaces where the computer detects the correctness of a given command based on brainwave analysis [94].

Overall, the holy grail of BCI is to implement a new complete and alternative pathway to restore lost locomotion [88].

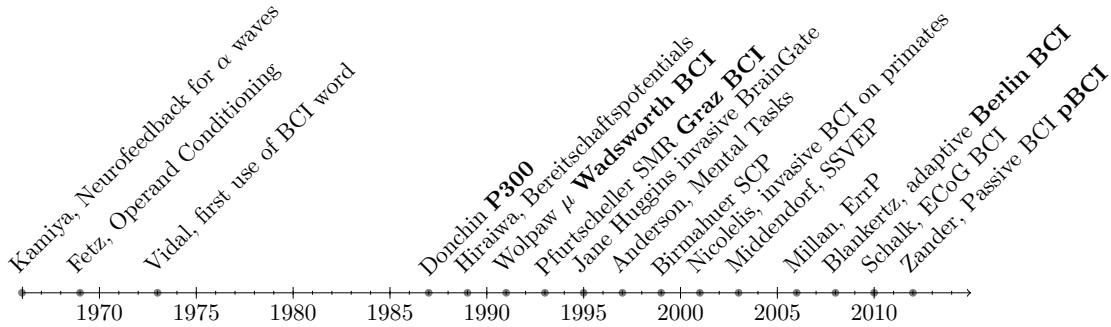


Figure 1 shows a brief chronology of the main events in BCI history, starting from the early works on Neurofeedback in the 70s and walking through the different paradigms. In recent years, this discipline has gained mainstream public awareness with worldwide challenge competitions like Cybathlon [68, 57] and even been broadcasted during the inauguration ceremony of the 2014 Soccer World Cup. New developments are approaching the out-of-the-lab high-bar and they are starting to be used in real world environments [25, 31]. Moreover, BCI research had rampantly been advanced accomplishing a BCI Society, a BCI Journal, BCI Award, annual conference meetings, practical applications, myriads of startups companies and even included in the Gartner list of Hype technologies [2].

From its root as assistive technology it has now expanded to include several application niches like Temporal induced disability, Neuroergonomics, early detection of human error, affective computing, biometric authentication, telepresence (improvement of haptic interface), cyberinfrastructure and assistive robotics. Intensive care units (ICU) and disorders of consciousness (DoC) [6] (detection of remaining brain activity in comatose patients) are recent disciplines where BCI is showing tremendous prospects and possible applications.

Their adoption as a clinical tool is still years ahead. Stroke Rehabilitation is the only area where clinical trials for BCI are being conducted. It is understood that the neurofeedback provided by a BCI interface improves the prognosis of motor rehabilitation [5].

BCI Definition (circa 2018)

Definition 1.0.1. *A system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external and internal environment [88].*

Despite all this, its primary objective, its core motive of moving into real applications for disabled people has yet to come [12, 38, 1]. They still lack the necessary robustness, and

its performance is well behind any other method of human computer interaction, including any kind of detection of residual muscular movement [19]. Among the many and current challenges of BCI [12] one which is still perennial is precisely their inability to be used and applied outside the BNCI community and specifically in clinical context.

Quoting experts in the field,

"We yet have an impractical and inaccessible exotica for very specific user groups" (Allison 2010)[?]

"Effectiveness of non-invasive BCI systems remain limited..." (Wolpaw 2011) [?]

"...to ponder if BCIs are really promising and helpful, or if they are simple a passing rod, reinforced by their sci-fi side..." (Lotte 2016)[?]

The feasibility of the system has been proved but there are several challenges in BCI that need to be tackled. They can be summarizing as increasing the ITR, the pervasive low signal-to-noise ratio of brainwaves, particularly of noninvasive signals [44], the reliability of the system, its portability, and the usability of the system [?], and at the same time decreasing the setup, the training and calibration time and the subject's inter/intra variability. The search for practical, relevant, and invariant *features* that convey good-enough information about the underlying cognitive process is still a goal to be achieved [61]. Ethical aspects of BCI [92] must also be considered and handled: cybersecurity threats and privacy concerns, agency and identity issues that might be occurring by deleterious plasticity with BCI users and the strict peg to the *Primum non nocere*¹ mandate.

1.1 Brain Computer Interface Model and Architecture

The draft architecture of a BCI system can be summarized in Fig 1.1. A volitional control, a will to transmit information, is exerted by a user. A brain imaging device captures his/her signals using a measurement modality. A signal acquisition module obtains the brainwaves and the information is digitalized and transmitted to a computer device. Signal preprocessing is applied to eliminate nuisances and artifacts and to enhance the Signal to Noise Ratio (SNR), or to apply spatial or frequency filters. In the next step, a *feature* is carefully constructed in order to differentiate at least between two different mental states. Finally a classification step is applied to derive the actual information bit out of the system.

¹*First, do not harm*, in reference to the Hippocratic Oath



Figure 1.1: General components of a BCI system.

An Application System uses this information to affect some external device. By visual or any other sensory means, the feedback is fed back to the user and a loop is finally closed.

The central point of this system is called the *Brain Machine Dilemma* [88]. The underlying idea is that the BCI system adapts to the user's thinking patterns but at the same time the brain is adapting to what the system is doing, and changing their own signals in the process. This is the reason why it is often called, a *co-adaptive system*, where two different intelligent devices, one biological and the other electronic, try to adapt to each other.

The basic model of any BCI is to take a multichannel digital signal $\mathbf{x}(n)$, and transform it to an output control signal $y(n)$ which can be a scalar or binary function. The BCI system can be modeled as the transformation T .

$$y(n) = T[\mathbf{x}(n)] \quad (1.1)$$

What a BCI system must do, is to take at least a single bit of information out of $y(n)$ and use that information to derive some action.

1.2 Signal Processing

From this signal processing point of view, BCIs are:

- Causal: $y(n) = f(\mathbf{v}(m))$, where $m \leq n$. The action of a BCI system depends on the history of the captured brainwaves.
- Dynamic: $y(n) = f(\mathbf{v}(m), \dot{\mathbf{v}}(m), \ddot{\mathbf{v}}(m), \dots)$. A BCI system is dynamic, where the output function do not depend only on the current value being observed, it does depend on its dynamic interactions.
- Time invariant: $y(n) = T[\mathbf{v}(n)] \Rightarrow y(n - k) = T[\mathbf{v}(n - k)]$. The output of a BCI system does not depend on the particular time frame where it is being used. However, Adaptive BCI, which do adapt to the user behavior are in general time variant.
- Nonlinear: a system is linear when $T[a_1\mathbf{v}(n) + a_2\mathbf{v}(n)] = a_1T[\mathbf{v}(n)] + a_2T[\mathbf{v}(n)]$. Due to brainwave complexity, BCI systems are not linear.
- Multirate or broadband [?]: The energy of brainwave spectrum is not confined to a certain band, and almost all frequency channels convey some information.

There are several filters that can be applied to the system to eliminate artifacts, enhance the signal, and to ease the detection of the discriminative information.

Static Filters like square or logarithmic were traditionally used in analog signal processing and are currently already embedded in the measuring device. Wiener and Kallman Filters are usually applied to invasive techniques [?]. The filter, particularly when it is linear, can be viewed as the matrix M in:

$$y(n) = MT[\mathbf{x}(n)] \quad (1.2)$$

Spatial filters are carefully adapted to the arrangement of sensors around or within the head and they emphasize the spatial structure of the information that is being captured. Derived from neuroscience research, locations on the head are structured according to neuroanatomical planes or axes and normally the brain, or the head, are divided in different anatomical regions (Figure 1.2).

Spectral Filters, on the other hand, do consider brainwaves as another digital signal, and they perform different transformations based on the spectral information contained within the signal $\mathbf{x}(n)$. They can be combined and aggregated creating *Filter Banks* to enhance signal quality.

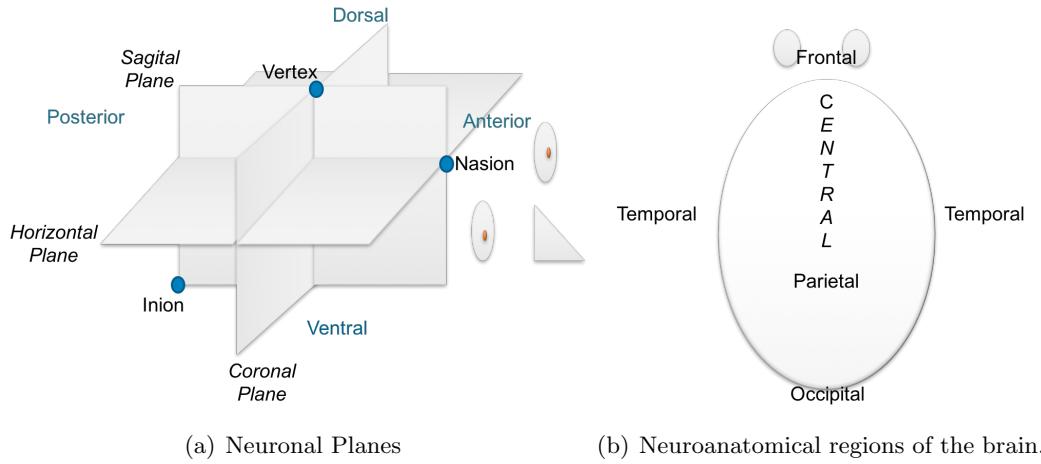


Figure 1.2: Neuronal Planes regularly used in neuroscience research. In BCI they are used to understand electrode location and spatial filters.

1.3 The Forward and Inverse Model

Brainwaves are obtained via sensors. Each one of them captures only a part or a version of the information. However, whatever is actually happening inside the brain can be only recovered indirectly from the *Sensor Space*. From there, the information can be traced back to the real landscape where the information source is located, inside the *Source Space*. This is a regular problem found in Engineering and it is not different in BCI. *Calculating* the signal on each a sensor from a projection of a known source of information from within the head is called *The Forward Problem*[60, 88] and doing the opposite, *estimating* the contributions of different sources to whatever activity is found on sensors is called *The Inverse Problem*. The latter is more relevant in BCI because it allows to determine source origins that can be mapped more directly to cognitive activities. However, this kind of problem is highly ill-posed and it is precisely where the majority of the efforts of this discipline are concentrated due to its complexity.

Particularly for noninvasive electrophysiological modalities, an additional problem makes thing harder. Due to its electromagnetic properties, the brain acts like conductive gel, and any signal that is generated inside the brain is irradiated to every direction and it can influence every sensor regardless of its position. This is called *Volume conduction* [53, 13] and can be visualized in Figure 1.3.



Figure 1.3: A source signal with positive/negative polarity is generated in a very specific region of the brain but due to volume conduction their influence affects a widespread area of the scalp where sensors are located (Image from Swartz Center for Computational Neuroscience)

1.4 Brain Imaging Technologies

The measuring technique determines the most important taxonomic differentiation in BCI, according to how they extract the information from the CNS Central Nervous System.

1. fNIRS: functional Near Infra Red Spectroscopy.
2. EEG: Electroencephalography
3. MEG: Magnetoencephalography
4. PET: Positron Emission Tomography
5. fMRI: functional Magnetic Resonance Imaging
6. ECoG: Electrocorticography
7. INR: Intracortical Neuron Recordings. Particularly LFP (iEEG, intracranial EEG[13]) and microelectrodes (Utah array).

ECoG and INR are invasive technologies that require some neurosurgery and an implantation of electrodes inside the skull the former, and inside the brain the latter. All the remaining imaging techniques are external or noninvasive. Hybrid BCI, or Brain Neural Computer Interface, are BCI devices that use not only signals from the CNS, they utilize any kind of available biosignal that can be volitionally modulated to transmit information (this is called dependant BCI). On the other hand, when the pace of the BCI is regulated by external stimulus it is called synchronous and when the user choose their own pace to transmit information, it is often called asynchronous or self-paced BCI.

Recent years have seen an incredible advance of Passive BCI, pBCI [93]. The original definition of BCI did not include Passive modalities but per definition 1.0.1 it is now part of this discipline. The important aspect is that passive technologies do not entail necessary the volitional requirement to transmit information. EEG-based passive BCI is a promising and advancing area of research and of commercial applications.

1.5 Electroencephalography

Above all, Electroencephalography (EEG), is the most widespread method to gather information from the CNS in a non-invasive way. They are of particular interest in BCI mainly

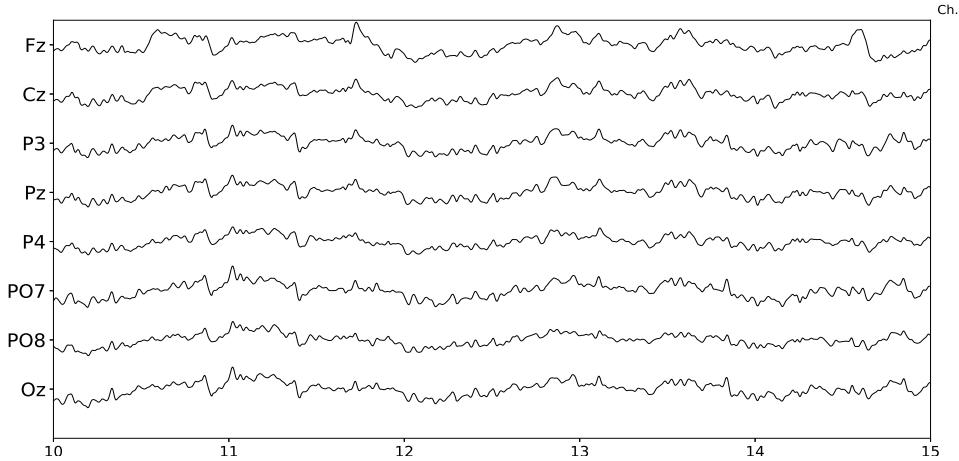


Figure 1.4: Sample EEG signal obtained from (g.Nautilus, g.Tec, Austria). Time axis is in seconds and five seconds are displayed. The eight channels provided by this device are shown.

because of their non-invasiveness, their optimal time resolution and acceptable spatial resolution. Moreover, they are portable, cheap, wearable and can be more easily integrated into fashionable designs aimed for real users, which prefer cap-like devices [32].

The Electroencephalography consists on the measurement of small variations of electrical currents over the scalp. This represents the summed activity of post-synaptic potentials PSPs of pyramidal neurons located perpendicular to the scalp [53]. Only one percent of synchronized activity of pyramidal neurons are stronger than the remaining desynchronized neurons [?] and explain ninety-nine percent of the signals obtained from EEG. This brain imaging technology is one of the most widespread used methods to capture brain signals and was initially developed by Hans Berger in 1924 and has been extensively used for decades to diagnose neural diseases and other medical conditions.

The first characterization that Dr. Berger detected was the Visual Cortical Alpha Wave, the *Berger Rythm* [35]. He understood that the amplitude and shape of this rhythm was coherently associated to a cognitive action (eyes closing). We should ask ourselves if the research advancement that came after that discovery would have happened if it weren't so evident that the shape alteration was due to a very simple and verifiable cognitive process.

The EEG signal is a highly complex multi-channel time-series. It can be modeled as a linear stochastic process with great similarities to noise [78]. It is measured in microvolts, and those slightly variations are contaminated with heavy endogenous artifacts and exogenous spurious signals.



Figure 1.5: International 10-20 system that standardize electrode locations over the scalp.



Figure 1.6: Consumer-grade digital electroencephalograph.

The device that captures these small variations in current potentials over the scalp is called the Electroencephalograph (Figure 1.6). Electrodes are located in predetermined positions over the head, usually embedded in saline solutions to facilitate the electrophysiological interface and are connected to a differential amplifier with a high gain which allowed the measurement of tiny signals. Although initially analog devices were developed and used, nowadays digital versions connected directly to a computer are pervasive. A detailed explanation on the particularities and modeling of EEG can be obtained from [33], and a description of its electrophysiological aspects from [27].

Overall, EEG signals can be described by their phase, amplitude, frequency and *waveform*. The following components regularly characterize EEG signals:

- Artifacts: These are signal sources which are not generated from the CNS, but can be detected from the EEG signal. They are called endogenous or physiological when they are generated from a biological source like muscles, ocular movements, etc., and

exogenous or non-physiological when they have an external electromagnetic source like line induced currents or electromagnetic noise[86]. Ambulatory studies or out-of-the lab studies introduces artifacts that are derived from the person movement from the FES and also from other devices in hybrid BCI, or multi-modal BCIs.

- Non-Stationarity: the statistical parameters that describe the EEG as a random process are not conserved through time, i.e. its mean and variance, and any other higher-order moments are not time-invariant [35].
- DC drift and trending: in EEG jargon, which is derived from concepts of electrical amplifiers theory, Direct Current (DC) refers to very low frequency components of the EEG signal which varies around a common center, usually the zero value. DC drift means that this center value drifts in time. Although sometimes considered as a nuisance that needs to get rid of, it is known that very important cognitive phenomena like Slow Cortical Potentials or Slow Activity Transients in infants do affect the drift and can be used to understand some particular brain functioning [72].
- Basal EEG activity: the EEG is the compound summation of myriads of electrical sources from the CNS. These sources generate a baseline EEG which shows continuous activity with a small or null relation with any concurrent cognitive activity or task.
- Inter-subject and intra-subject variability: EEG can be affected by the person's behavior like sleep hygiene, caffeine intake, smoking habit or alcohol intake previously to the signal measuring procedure [22].

Regarding how the EEG activity can be related to an external stimulus that is affecting the subject, it can be considered as

- Spontaneous: generally treated as noise or basal EEG.
- Evoked: activity that can be detected synchronously after some specific amount of time after the onset of the stimulus. This is usually referred as time-locked. In contrast to the previous one, it is often called Induced activity.

Additionally, according to the existence of a repeated rhythm, the EEG activity can be understood as

- Rhythmic: EEG activity consisting in waves of approximately constant frequency. It is often abbreviated RA (regular rhythmic activity). They are loosely classified by their frequencies, and their naming convention was derived from the original naming used by Hans Berger himself:
 - Alpha Waves (10 Hz)
 - Delta (0-4 Hz)
 - Theta (4-8 Hz)
 - Sigma (12-16 Hz)
 - Beta (12-30 Hz)
 - Gamma (30-100 Hz)
 - Omega (60-120 Hz)
 - Rho (250 Hz) hippocampal
 - Sigma Thalamocortical burst (600 Hz)
- Arrhythmic: EEG activity in which no stable rhythms are present.
- Dysrhythmic: Rhythms and/or patterns of EEG activity that characteristically appear in patient groups and rarely seen in healthy subjects.

The number of electrodes and their positions over the scalp determines a Spatial Structure: signal elements can be generalized, focal or lateralized, depending on in which channel (i.e. electrode) they are found.

1.6 BCI EEG Paradigms

BCI Paradigms are referred to noninvasive EEG-based BCI configurations that can be used to transmit volitional information. The popularity of EEG (71.2% of the BCI projects submitted to BCI Award 2016 were with EEG) [25] pushed the adoption of paradigms exclusively for noninvasive BCI. Their chronology can be found in Figure 1. They are

1. Steady State Visual Evoked Potentials
2. Bereitschaftspotentials, Readiness Potential or Movement-Related Potentials
3. Motor Imagery

4. ERD/ERS: Event Related
5. Wadsworth BCI
6. Graz BCI
7. Selective Attention
8. P300
9. N400
10. Mental Tasks
11. Operant Conditioning
12. Slow Cortical Potentials
13. Berlin BCI

1.7 State of the Art of BCI Algorithms for EEG processing

According to general layout of any BCI, Figure 1.1, specific algorithms or techniques are derived for both the Feature extraction and classification step.

The most relevant features used in BCI are:

- Time points: the sequence of time series, often, concatenated in time or space.
- Band Power: frequency based features.
- Complexity: based on complexity measurements like entropy, fractal.
- Statistical: AR parameters, covariances matrix.

The most successfull used and verified classification methods for BCI [45] can be described as linear versions of popular Machine Learning tools. Particularly, Support Vector Machines SVM, Linear Discriminant Analysis LDA and its variant SWLDA. This one was also relevant for two reasons: the first is that the stepwise identification of features improves the selection criteria and also the spatial filter that this procedure encompass. Additionally, and more from a more pragmatic perspective, this method was included in the popular BCI2000 [?] package and was the default option for anyone doing ERP identification. Spatial Filters have

also being incorporated and have shown substantial improvement in classification accuracies. The now classical Common Spatial Patterns CSP for the identification of Motor Imagery as well as the xDAWN algorithm for P300 identification.

Recent years (circa 2018) have seen the evolution of the methodology but the focus was not centered on any particular classification algorithm. Instead how they are used became much more important [44].

- Ensemble Classifiers: SVM ensembles [?] and variants of Random Forest [?]. Features are segmented and divided and the forest performs a classification step on each part and maximizes classification accuracies.
- Cross-Paradigm BCI: the use of Reinforced Signal RS with ErrP feedback or the use of SSVEP in combination with P300 detection [?].
- Adaptive Classifiers: the parameters of the classifiers are adapted continuously and online adapting to the natural variation of the EEG signals [44].
- Transfer Learning: transfer the calibration information obtained by users to new subjects. This aims to eases the issue of the intra-subject variability in BCI .
- RGC: Riemann Geometry Classifiers
- Tensor-based BCI
- Deep Learning: heavily tried but without significant success.

1.8 EEG Waveform Analysis

1.8.1 EEG Waveform Characterization

The shape of the signal, the waveform, can be defined as the graphed line that represents the signal's amplitude plotted against time. It can also be called EEG biomarker, EEG pattern, motifs, signal shape, signal form and a morphological signal [35].

The signal context is crucial for waveform characterization, both in a spatial and in a temporal domain [35]. Depending on the context, some specific waveform can be considered as noise while in other cases is precisely the element which has a cognitive functional implication.

A waveform can have a characteristic shape, a rising or falling phase, a pronounced plateau or it may be composed of ripples and wiggles. In order to describe them, they are characterized by its amplitude, the arch, whether they have (non)sinusoidal shape, by the presence of an oscillation or imitating a sawtooth (e.g. Motor Cortical Beta Oscillations). The characterization by their sharpness is also common, particularly in Epilepsy, and they can also be identified by their resemblance to spikes (e.g. Spike-wave discharge).

Other depictions may include, subjective definitions of sharper, arch comb or wicket shape, rectangular, containing a decay phase or voltage rise, peaks and troughs, short term voltage change around each extrema in the raw trace. Derived ratios and indexes can be used as well like peak and trough sharpness ratio, symmetry between rise and decay phase and slope ratio (steepness of the rise period to that of the adjacent decay period). For instance, wording like "Central trough is sharper and more negative than the adjacent troughs" are common in the literature.

Other regular characterizations which are based on shape features may include:

- Attenuation: Also called suppression or depression. Reduction of amplitude of EEG activity resulting from decreased voltage. When activity is attenuated by stimulation, it is said to have been "blocked" or to show "blocking".
- Hypersynchrony: Seen as an increase in voltage and regularity of rhythmic activity, or within the alpha, beta, or theta range. The term suggest an increase in the number of neural elements contributing to the rhythm and a synchronization of neurons with similar firing patterns [13].
- Paroxysmal: Activity that emerges from background with a rapid onset, reaching (usually) quite high voltage and ending with an abrupt return to lower voltage activity.
- Monomorphic: Distinct EEG activity appearing to be composed of one dominant activity
- Polymorphic: distinct EEG activity composed of multiple frequencies that combine to form a complex waveform.
- Transient. An isolated wave or pattern that is distinctly different from background activity.

The traditional clinical approach consists in analyzing the paper strip that is generated by the plot of the signal obtained from the device. Expert technician and physicians

analyze visually the plots looking for specific patterns that may give a hint of the underlying cognitive process or pathology. Atlases and guidelines were created in order to help in the recognition of these complex patterns. Even Video-electroencephalography scalp recordings are routinely used as a diagnostic tools [24]. The clinical EEG research has also focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG *graphoelements* [72].

Sleep Research has been studied in this way by performing Polysomnographic recordings (PSG) [69], where the different sleep stages are evaluated by visually marking waveforms or graphoelements in long-running electroencephalographic recordings, looking for patterns based on standardized guidelines. Visual characterization includes the identification or classification of certain waveform components, or transient events, based on a subjective characterization (e.g. positive or negative peak polarity) or the location within the strip. It is regular to establish an amplitude difference between different waveforms from which a relation between them is established and a structured index are created (e.g. sleep K-Complex is well characterized based on rates between positive vs negative amplitude) [81]. Other relevant EEG patterns for sleep stage scoring are alpha, theta, and delta waves, sleep spindles, polysplindles, vertex sharp waves (VSW), and sawtooth waves (REM Sleep).

Moreover, EEG data acquisition is a key procedure during the assessment of patients with focal Epilepsy for potential seizure surgery, where the source of the seizure activity must be reliably identified. The onset of the Epileptic Seizure is defined as the first electrical change seen in the EEG rhythm which can be visually identified from the context and it is verified against any clinical sign indicating seizure onset. The interictal epileptiform discharges (IEDs) are visually identified from the paper strip, and they are also named according to their shape: spike, spike and wave or sharp-wave discharges[11].

1.8.2 EEG Waveform Analysis Algorithms

Shape or waveform analysis methods are considered as nonparametric (in opposition to statistical or dynamical models). They explore signal's time-domain metrics or even derive more complex indexes from it [79].

One of the earliest approach to automatically process EEG data is the Peak Picking method. Although of limited usability, peak picking has been used to determine latency of transient events in EEG [36, 95]. Straightforward in its implementation, it consists in selecting a component, a simple component based on the expected location of its more

prominent deflection [58]. Evoked Potentials (EPs) and Event Related Potentials (ERPs) are transient component that may arise as a brain response to an external visual, tactile or auditory stimulus. Particularly, EPs are regularly used to assess auditory response in infants. ERPs are precisely characterized in this manner, where the name of many of the EEG features evoke directly a peak within the component, e.g. P300 or P3a, P3b or N100. This leads to a natural procedure to classify them visually by selecting appropriate peaks and matching their positions and amplitudes in an orderly manner. The letter provides the polarity (Positive or Negative) and the numbering shows the time referencing the stimulus onset, or the ordinal position of each peak (first, second, etc).

A related method is used in [4] where the area under the curve of the EEG is summarized to derive a feature. This was even used in the seminal work of Farwell and Donchin on P300 [21, 88]. Additionally, a logarithmic graph of the peak-to-peak amplitude which is called amplitude integrated EEG (aEEG) [74] is used nowadays in Neonatal Intensive Care Units.

Other works on EEG explored the idea to extend human capacities analyzing EEG waveforms [23] where a feature from the amplitude and frequency of its signal and its derivative in time-domain is used. Moreover, other works explored the use of Mathematical Morphology [90], where the time-domain structure of contractions and dilations were studied. Finally the proposals of Burch, Fujimori, Uchida and the Period Amplitude Analysis (PAA) [82] algorithm are few of the earliest proposals where the idea of capturing the shape of the signal were established.

Pursuit algorithms refer, in their many variants, as blind source separation [?] techniques that assume the EEG signal as a linear combination of different sparse sources extracted from a template's dictionaries. Matching Pursuit *MP* [50], the most representative of this algorithms, is a greedy variant that decomposes a signal into a linear combination of waveforms, called atoms, that are well localized in time and frequency [16]. This method has been used to identify epileptogenetic patterns from EEG traces [83].

Another method that explores the waveform is Bond and Pompe Permutation Entropy [7]. This has been extensively used in EEG processing, with applications on Anesthesia, Sleep Stage evaluation and increasingly for Epilepsy pre-ictal detection . This method generates a code based on the orderly arrangement of sequential samples, and then derives a metric which is based on the number of times each sequence is found on the signal. This numeric value can be calculated as information entropy [54].

A related method is Slope Horizontal Chain Code and Slope Chain Code (SCC) [4]. This

algorithm proceeds by generating a coding scheme from a sequence of sample points. This encoding is based on the angle between the horizontal line on a 2D-plane and any segment produced by two consecutive sample points, regarding them as coordinates on that plane. Similar works were provided in Local Binary Patterns (1-D LNBP, 1D-LBP and LBP)[34] algorithms. Finally, the MIDS Merging of Increasing and Decreasing Sequences [96] do not generate a feature but it provides a filter or downsampling scheme which is based on the waveform structure.

All these methods provide a feature that can be used as a template, whereas all of them are based on metrics that can be extracted from the shape of the signal. These features can be used to create dictionaries or template databases. These templates provide the basis for the pattern matching algorithm and offline classification.

Chapter 2

From signals to images

This chapter describes the procedure to plot an image from the digital EEG signal. This image is used to extract a feature which represents the waveform, the structure of the signal on a plot. By analyzing this feature, we hypothesize that the underlying cognitive process can be detected and that it can be used to implement a brain-computer communication device.

2.1 Electroencephalographic Plotting

The plotting of the EEG is intrinsically mixed with the nuisances of the electroencephalography itself. Plotting proceed by using a chart recorded with a single pen [37]. Voltages are represented on a vertical axis while time is represented on the horizontal axis, in a Cartesian arrangement.

1. Sensitivity: also termed gain due the amplification procedure. Its units are $\frac{mV}{mm}$. In the digital form, it is $\frac{\mu V}{pixel}$.
2. Epoch/Paper speed: the time span that is represented in a single screen. For paper strips it was used to be 10s (Figure FIG). In the digital version is $\frac{\lambda}{pixel}$.

Logarithmic plotting, montage, calibration (cite Electroencphalography for empilepsy society)

Neuroimaging

With the advent of digital computers and the digital revolution, Plotting has become imaging. Neuroimaging (Cite book Rodrigo Q Q) means mapping activity or structure to neuroanatomical regions (see Figure 1.2).

There are currently three categories of neuroimaging: structural, functional, and chemical.

- Structural Neuroimaging Any technique that images structures of the brain. This would include CT (Computed Tomography), MRI (Magnetic Resonance Imaging), and DTI (Diffusion Tensor Imaging).

CT scanning is non-invasive uses x-rays to image tissue density. It is very rapid and can detect cerebral hemorrhaging in the early (acute) stage. It is most often, therefore, used for medical purposes.

Structural MRI is non-invasive and often provides better contrast resolution than CT with similar (and again, often better) spatial resolution. Unlike CT, structural MRI provides excellent tissue delineation, allowing users to visualize boundaries between grey and white matter in the brain, for example. Structural MRI is often used in neuroimaging to calculate volume of different brain regions or to define regions of brain damage or tumor.

DTI is non-invasive and can be done on most research MRI scanners. It involves using a special scanning and reconstruction sequence to image the flow (or, more specifically, constraints in the flow) of water through the brain. Because water flow is constrained by the axons (white matter) in the brain, it can be used to image large axonal connections between brain regions.

- Functional Neuroimaging Any technique that quantifies some metric of brain activity. This would include EEG (ElectroEncephaloGraphy), MEG (MagnetoEncephaloGraphy), fMRI (functional MRI), PET/SPECT (Positron Emission Tomography/Single Positron Emission Computed Tomography), NIRS (Near-InfraRed Spectroscopy), and, to a certain extent, TMS (Transcranial Magnetic Stimulation) and TDCS (Transcranial Direct Current Stimulation), along with several others.

2.2 Signal to Image transformation

The EEG signal may be represented by

$$\mathbf{x}(n) = x(n, c) \quad (2.1)$$

where n are sample points digitalized at sampling frequency F_s . This is a multichannel signal, for c varying between 1 and C . Each one of this channels is assigned a name according

to the 10-20 international system, and there are C available channels. The sample index n varies between 1 and N . The span of the signal as λ is the inverse of the sampling frequency.

To extract features from an image, first you need an image. And this image needs to represent the underlying signal. The straightforward way to do it, reproducing the traditional analog or digital EEG, is to draw a line on contrast background. The line represents the voltage amplitude of the corresponding channel in relation to a zero-level $z(c)$, with a positive deflection going upwards (towards the zero value in the image coordinate system) and downwards for negative deflection (Figure ??). If only two colors are used, this image is a black-and-white binary image. In principle, color selection is completely arbitrary (white for the line, black for the background), but it has some implications in terms of the feature extraction procedure that we will describe later.

This chapter mostly deal with the coordinates transformation that need to be enforced while converting the signal into a plot. Figure ?? shows the image coordinate system where the (z_1, z_2) represents the horizontal and vertical location, and the $(0, 0)$ value is the upper-left position of the image.

In how many ways EEG signals can be mapped into 2D greyscale or binary images ?

$$I(x, y, n) = 0 \quad (2.2)$$

which is a three dimensional surface.

Channel by Channel binary image The standard plotting, on a black-and-white image with lines representing voltage amplitude.

$$I(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = n; z_2 = x(n, c) + z(c) \\ 0 & \text{otherwise} \end{cases} \quad (2.3)$$

Channel by channel grey color image The voltage amplitudes are represented by grey scale colors, that could range between 0 and 255. The function $\phi(\cdot)$ is a bounded linear mapping.

$$I(z_1, z_2) = \begin{cases} \phi(x(n, c)) & \text{if } z_1 = n; z_2 = z(c) \\ 0 & \text{otherwise} \end{cases} \quad (2.4)$$

Multichannel Full grey color image The image is grey-scale. Voltage amplitudes are represented by the pixel content and each channel is represented on the vertical axis. The

height of the signal is equal to the number of channels. This is used in Neuroimaging plots of ERP events.

$$I(z_1, z_2) = \begin{cases} \phi(x(n, c)) & \text{if } z_1 = n; z_2 = c \\ 0 & \text{otherwise} \end{cases} \quad (2.5)$$

Multichannel Stationary Binary image The horizontal axis of the image is not time, but it is channels instead. In this representation different contributions from different channels can be explored at the same time, but time dynamics is lost.

$$I(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = c; z_2 = x(n, c) + z(n) \\ 0 & \text{otherwise} \end{cases} \quad (2.6)$$

Multichannel Stationary Grey-scale image This is a variant of the previous one, where the horizontal axis represent the channel. In this form, the intensity of the contribution of each channel is represented by the grey-scale pixel value. Combined with head models and forward projection solutions this is the approach used to represent scalp heatmaps (See figure 3, MNE).

$$I(z_1, z_2) = \begin{cases} \phi(x(n, c)) & \text{if } z_1 = c; z_2 = z(n) \\ 0 & \text{otherwise} \end{cases} \quad (2.7)$$

Channel by channel full grey color image This is similar to a raster plot but the greyscale image representing voltages in pixel intensities is repeated H times, which is the height of the image. The selection of this value is arbitrary.

$$I(z_1, z_2) = \begin{cases} \phi(x(n, c_i)) & \text{if } z_1 = n; z_2 = H \\ 0 & \text{otherwise} \end{cases} \quad (2.8)$$

This last representation has the important property that $\text{LoG}(I(x, 0)) = \text{LoG}(x(n, c))$.

2.3 EEG Signal Plot

A binary image plot $I^{(c)}$ can be constructed according to

$$I^{(c)}(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = \gamma n; z_2 = \tilde{x}(n, c) + z(c) \\ 0 & \text{otherwise} \end{cases} \quad (2.9)$$

with 255 being white and representing the signal's voltage and 0 for black which is the background contrast, conforming a black-and-white plot of the signal. Pixel arguments $(z_1, z_2) \in \mathbb{N} \times \mathbb{N}$ iterate over the width and height of the image plot with $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$.

The transformation from signal to image is continuously repeated, and many images need to be produced for each segment of the EEG signal under analysis. Hence, the following question arises? How to determine the size of all the images so that they can be effectively compared automatically ? The first way is to regularize the signal and fit it in an (almost-)equal size for all image. An alternative choice is to autoscale every image according to the zero-level position.

2.3.1 Standardized plotting

There are many ways to regularize the signal, but the *z-score* is widely used and accepted to do this (ref z-score in BCI).

The standardization is defined for $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$ by doing

$$\tilde{x}(n, c) = \frac{(x(n, c) - \bar{x}(c))}{\hat{\sigma}(c)} \quad (2.10)$$

where $x(n, c)$ is the multichannel EEG signal segment for the sample point n and for channel c . The values

$$\bar{x}(c) = \frac{1}{n_{max}} \sum_{n=1}^{n_{max}} x(n, c)$$

and

$$\hat{\sigma}(c) = \left(\frac{1}{n_{max} - 1} \sum_{n=1}^{n_{max}} (x(n, c) - \bar{x}(c))^2 \right)^{\frac{1}{2}}$$

are the mean and estimated standard deviation of $x(n, c), 1 \leq n \leq n_{max}$, for each channel c .

The zero-level $z(c)$ is thus, the image vertical position where the signal's zero value has to be situated in order to fit the entire signal within the image for each channel c :

$$z(c) = \left\lfloor \frac{\max_n \tilde{x}(n, c) - \min_n \tilde{x}(n, c)}{2} \right\rfloor - \left\lfloor \frac{\max_n \tilde{x}(n, c) + \min_n \tilde{x}(n, c)}{2} \right\rfloor \quad (2.11)$$

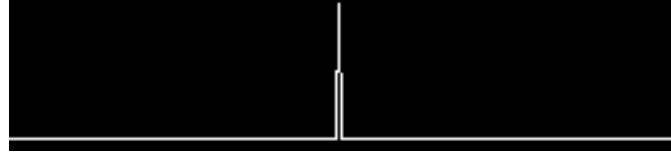
where the minimization and maximization are carried out for n varying between $1 \leq n \leq n_{max}$, and $\lfloor \cdot \rfloor$ denote the rounding to the smaller nearest integer of the number. In brief, this value represent the vertical location on the image where the signal goes to zero.

2.3.2 Autoscaled plotting

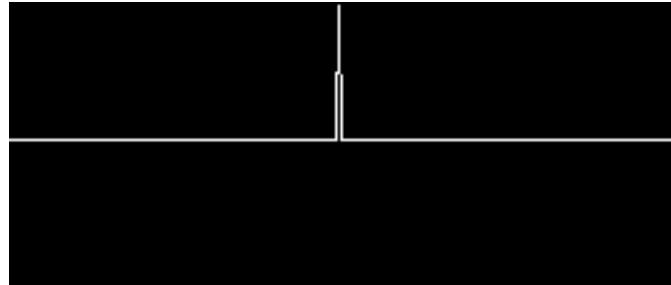
This plotting scheme allows each image to adapt to the underlying signal. The height is set at twice the value of the zero-level, and the signal mean is subtracted from the signal, which is a vertical displacement.

$$\tilde{x}(n, c) = x(n, c) - \bar{x}(c) \quad (2.12)$$

Figure 2.1(b) shows the results of the plotting for an impulse signal.



(a) A signal pulse determines the height of the plotted image.



(b) The plotted image is twice the zero-level. In this case

Figure 2.1: Signal plotting schemes.

2.3.3 Image Size

Height

The height of the image is calculated according to the peak-to-peak amplitude of the signal,

$$H_y = \max x(n, c) - \min x(n, c) \quad (2.13)$$

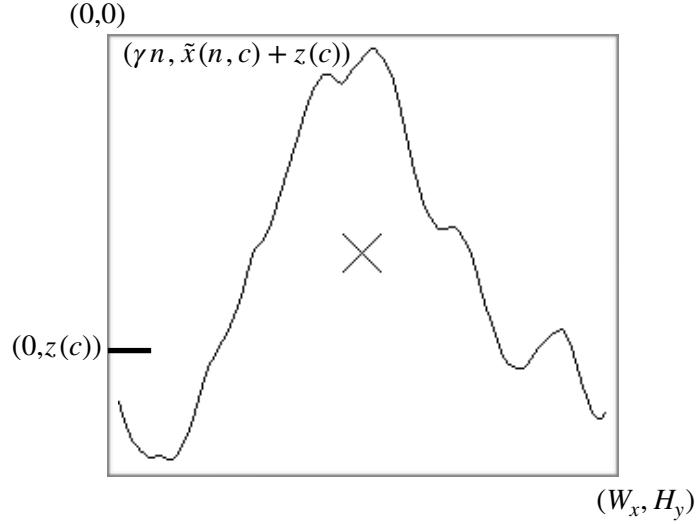


Figure 2.2: A K-Complex transient event is shown on the image

while for the Autoscalable version, it is just twice the value of the zero-level.

$$H_y = 2 z(c) \quad (2.14)$$

Width

The width on the other hand is obtained based on the span of the signal segment, scaled by the γ_t time factor,

$$W_x = \gamma_t N \quad (2.15)$$

2.3.4 Pixelation

EEG time-series are floating-point numbers and the image is constructed based on discrete and integer pixels. To map one to the other you need to account for the rounding.

$$\tilde{x}(n, c) = \lfloor \gamma \tilde{x}(n, c) \rceil \quad (2.16)$$

On the horizontal axis, z_1 , no discretization is needed because time is already in sample units.

2.3.5 Interpolation

Equation 2.9 produces a set of isolated pixels over the image. To produce the plot $I^{(e)}$, the Bresenham [10, 63] algorithm is used to interpolate straight lines between each pair of consecutive pixels.

Figure where the interpolation is shown.

However, as seen in Figure, it can lead to very sharp edges around the sample pixels. This can lead to a quantization of histogram gradients, so another option is to use an interpolated version. Instead of just skipping time points values, these values are interpolated according to a linear quadratic or cubic interpolation, which smooths the curve around each point.

Figure where the interpolation is improved.

(based on Matlab resample function) .resample applies an antialiasing FIR lowpass filter to x and compensates for the delay introduced by the filter.

Special care must be taken to avoid artifacts around the edges of the signal, so a window is also necessary to avoid this (like hamming).

2.3.6 Resolution

According to the plotting scheme, a resolution is established between pixel images and signal properties.

On the horizontal axis of the image, one pixel is equivalent to

$$1P_x \equiv \frac{1}{F_s \lambda \gamma_t} [\text{s}] \quad (2.17)$$

where F_s is the sampling frequency in Hertz, λ is the span of the segment (in seconds), and γ_t is the scale factor. This gives a value in seconds. For example, for Figure 2.2, the sampling frequency is 200Hz, the span is 0.65s and $\gamma_t = 1$, which gives a resolution of $1P_x \equiv 0.0077s$.

Consistently, on the vertical axis, one pixel is analogous to

$$1P_y \equiv \frac{1}{\gamma} [\mu\text{V}] \quad (2.18)$$

where γ is the signal scale. As EEG time-series are digitalized in μV , this the unit of choice. In Figure 2.2, 1 vertical pixel represents exactly $1\mu\text{V}$.

Chapter 3

The Histogram of Gradient Orientations of Signal Plots

In this section the generalities of the method will be described.

3.1 Introduction

Image transformation and variants to transform a signal into an image.

sinuplot, spectrogram, scalogram

The research that encompass how to extract information

The work of Edelman, Intrator and Poggio 1997 how the visual cortex sees features was the inspiration to the use of the histogram of gradient orientations to

3.2 Feature Extraction: Histogram of Gradient Orientations

On the generated image I , a keypoint **kp** is placed on a pixel (x_{kp}, y_{kp}) over the image plot and a window around the keypoint is considered. A local image patch of size $S_p \times S_p$ pixels is constructed by dividing the window in 16 blocks of size $3s$ each one, where s is the scale of the local patch and it is an input parameter of the algorithm. It is arranged in a 4×4 grid and the pixel **kp** is the patch center, thus $S_p = 12s$ pixels.

A local representation of the signal shape within the patch can be described by obtaining the gradient orientations on each of the 16 blocks and creating a histogram of gradients. This technique is based on Lowe's SIFT [47] method, and it is biomimetically inspired in how the visual cortex detects shapes by analyzing orientations [20]. In order to calculate the histogram, the interval $[0 - 360]$ of possible angles is divided in 8 bins, each one at 45 degrees.

Hence, for each spacial bin $i, j = \{0, 1, 2, 3\}$, corresponding to the indexes of each block $B_{i,j}$, the orientations are accumulated in a 3-dimensional histogram h through the following equation:

$$h(\theta, i, j) = 3s \sum_{\mathbf{p}} w_{\text{ang}}(\angle J(\mathbf{p}) - \theta) w_{ij} \left(\frac{\mathbf{p} - \mathbf{k}\mathbf{p}}{3s} \right) |J(\mathbf{p})| \quad (3.1)$$

where \mathbf{p} is a pixel from within the patch, θ is the angle bin with $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$, $|J(\mathbf{p})|$ is the norm of the gradient vector in the pixel \mathbf{p} and it is computed using finite differences and $\angle J(\mathbf{p})$ is the angle of the gradient vector. The scalar $w_{\text{ang}}(\cdot)$ and vector $w_{ij}(\cdot)$ functions are linear interpolations used by [47] and [85] to provide a weighting contribution to eight adjacent bins. They are calculated as

$$w_{ij}(\mathbf{v}) = w(v_x - x_i)w(v_y - y_i) \quad (3.2)$$

$$w_{\text{ang}}(\alpha) = \sum_k w\left(\frac{8\alpha}{2\pi} + 8r\right) \quad (3.3)$$

where x_i and y_i are the spatial bin centers located in $x_i, y_i = \{-\frac{3}{2}, -\frac{1}{2}, \frac{1}{2}, \frac{3}{2}\}$, $\mathbf{v} = (v_x, v_y)$ is a dummy vector variable and α a dummy scalar variable. On the other hand, r is an integer that can vary freely which allows the argument α to be unconstrained in terms of its values in radians. The interpolating function $w(\cdot)$ is defined as:

$$w(z) = \max(0, |z| - 1) \quad (3.4)$$

These binning functions conform a trilinear interpolation that has a combined effect of sharing the contribution of each oriented gradient between their eight adjacent bins in a tridimensional cube in the histogram space, and zero everywhere else.

Lastly, the fixed value of 3 is a magnification factor which corresponds to the number of pixels per each block when $s = 1$. As the patch has 16 blocks and 8 bin angles are considered, a feature called *descriptor* of 128 dimension is obtained.

Fig. 6.3 shows an example of a patch and a scheme of the histogram computation. In (A) a plot of the signal and the patch centered around the keypoint is shown. In (B) the possible orientations on each patch are illustrated. Only the upper-left four blocks are visible. The first eight orientations of the first block, are labeled from 1 to 8 clockwise. The orientations of the second block $B_{1,2}$ are labeled from 9 to 16. This labeling continues left-to-right, up-down until the eight orientations for all the sixteen blocks are assigned.

They form the corresponding **kp**-descriptor of 128 coordinates. Finally, in (C) an enlarged image plot is shown where the oriented gradient vector for each pixel can be seen.

3.3 Keypoint Location

3.4 Oscillatory Processes

3.5 Transient Events

3.6 Mapping Functions

3.7 Implementation

3.7.1 Matlab

3.8 Classification

NBNN

Chapter 4

Alpha Wave: inhibition signal

This is awesome!

Berger

4.1 Introduction

Alpha Waves are 8-12 Hz signals, physiologically well consistent across subjects, and they are associated with synchronous inhibitory processes and attention shifting, more prominent while the eyes are closed [70]. The results of applying a 8-12 Hz band-pass filter and calculating the Power Spectral Density (PSD) across subjects for each channel can be seen in Fig. 5.1, where the values obtained for class 2 (eyes closed) are higher than the values for class 1 (eyes open), showing that the differentiation information is contained in the frequency-domain.

They tend to be more prominent and appear stronger in occipital regions. We process this Dataset with a 8-12 Hz band-pass filter, and calculate the Power Spectral Density across subjects for each channel. In Fig. ?? it can be seen that the PSD value is greater for the class 2 (eyes closed), showing also that the differentiation information is contained mostly in the frequency-domain.

Alpha Waves are 10 Hz signals, physiologically consistent across subjects, and they are associated with synchronous inhibitory processes and attention shifting [70]. They tend to be more prominent while the eyes are closed and appear stronger in occipital regions (O_1 and O_2 according to the 10-20 system [89, 77]). As can be seen in Fig. ??, if we process the Drowsiness dataset with a 8-12Hz band-pass filter and calculate the average power spectral density across subjects and for each channel, we can see how clearly the value corresponding to class 2 (eyes closed) is always higher than the value for class 1 (eyes open), confirming the

expected result. This also verifies how the differentiation information is contained mostly in the frequency-domain.

4.2 Materials and Methods

First, an in-house dataset (see [12] for details) which characterizes one of the most prominent cognitive phenomena, occipital visual alpha rhythm Event Related Synchronization on closed eyes, was used. We gather the first dataset using the EEG EPOC Emotiv Headset using the C++ SDK library provided by the manufacturer and an in-house developed program. The device has 14 channels, and a sampling rate of 128 Hz [77]. Ten random healthy subjects between ages 20-50 were recruited and they accepted to wear the device and to participate in the experiments. A 30 minutes procedure was required to adjust the headset to each user, in order to decrease the impedance on each electrode. Once the set up was finished, each subject was instructed to sit in a relaxed position. Subsequently, she/he was instructed to watch the screen for 15 seconds, trying to avoid, as much as possible, to abruptly move its body or head. During that time, a single-trial of 10 seconds-length window of EEG signals data was transferred to a PC and logged into standard binary files. After a 5 minutes pause, the subject was asked to close the eyes avoiding any movement while keeping the same pose for another batch of 15 seconds. Again, 10 seconds of EEG information were transferred and logged into the PC. This finally gave us a sample of 10 subjects, 2 trial per subject, one for each class, composed of 14 channels, 10-seconds length or 1280 samples per window.

For this dataset, 10 windows of 1s for each class were gathered from 10 healthy subjects. Descriptors were extracted from all the generated images, from both classes, and they were used to classify images from the same set.

Although EPOC Emotiv is a commercial device, more apt as HCI tool, it is possible to detect fairly some BCI components.

Additionally, we tested the method against the public dataset of the AlphaNet effort published by Schwartz group.

For the first two datasets, as the sampling frequency of both datasets is similar, Image and SIFT Descriptor Scale were adjusted to delta and gamma to 1.

What is remarkable, and will be is that the information is contained in the frequency domain. How it was possible to obtain a fairly good accuracy with this method given that important point ? The key here is the classification algorithm that was used across this

thesis. This is because the local information obtained from each descriptor "help" to balance a tendency of how the synchronous waves all behave, and that information get loaded into the class structure that is later exploited by the classification method.

Dataset II - BCI Competition 2003 IV *self-paced 1s*

We validated our method against the "BCI Competition 2003, dataset IV *self-paced 1s*" [8]. This dataset is composed of 28 channels, in 416 epochs of 50 samples per epoch (500 ms length at 100 Hz) each one with the corresponding label, where subjects were asked to type at will a letter on a keyboard with the right or left index finger. It is based on the Bereitschaftspotential [75], which is a Slow Cortical Potential, particularly a slow change in voltages towards a negative potential drift, around 1000-500 ms before the onset of the self-initiated movement. In this case, the information lies strongly on the time-domain.

This dataset was recorded from a healthy subject during a no-feedback session. She/he sat in a normal chair with relaxed arms resting on the table and fingers in the standard typing position at the computer keyboard. The task was to press with the index and little fingers the corresponding keys in a self-chosen order and timing 'self-paced key typing'. The experiment consisted of 3 sessions of 6 minutes each. All sessions were conducted on the same day with some minutes break in-between. Typing was done at an average speed of 1 key per second.

4.3 Results

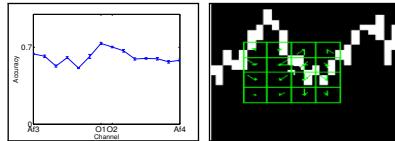


Figure 4.1: (Left) A detailed image of a SIFT Descriptor over a plotted signal is shown. (Right) Classification Accuracy for discriminating windows of 1s (128 samples) of EEG signals from 10 subjects with their eyes open and closed. The classification accuracy is maximum on occipital channels O1 and O2. The descriptor size is 12x12 pixels which corresponds to a variation of 12 microvolts in the signal amplitude during 0.09 s

Regarding the first datasets, results were shown in Fig. 2 (right) where the classification accuracy is shown after applying a 10-Fold Cross Validation procedure on the entire set of labeled descriptors. Descriptors from different subjects were used as part of the different

training set to classify unknown images, so the obtained accuracy level was subject-independent. Moreover, a classification level with average above 70% was obtained in Occipital channels.

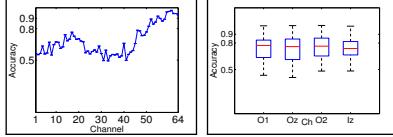


Figure 4.2: Classification Accuracy for discriminating windows of 1s (160 samples) of EEG for Alpha Waves differences between subjects with eyes opened and closed. The descriptor size is 12x12 pixels. (Left) 10-Fold cross validated accuracies for one subject. (Right) Average accuracy levels for 25 subjects for the occipital channels. Medians were above 75%.

For the second dataset, an accuracy median higher than 70% for 25 subjects, also on occipital channels O1, Oz, O2 and Iz (numbered 61 to 64) was obtained while discriminating Runs 1 and 2 (Baseline eyes open vs Baseline eyes closed). Fig. 3 shows the 10-Fold Validated Accuracy for one random subject [6,7], where a higher accuracy in the classification of the signals can also be seen with occipital channels.

4.4 Conclusion

This results was surpassing. We are using a method which is based on the waveform to detect a process which happens to be more prominent in spectrum. But this shows at the same time the complex relationship between time and frequency. The shape in time of a oscillatory process prominent in frequency is clearly evident. This goes in line with the fact that alpha waves can be seen in the EEG, and are basic tools of clinical diagnosis.

Chapter 5

Motor Imagery

5.1 Introduction

Motor Imagery is an EEG or ECoG based BCI paradigm originated on changes of SMR, sensorimotor rhythms, that are altered when a person engages in motor behavior, but it can also be elicited when a person imagines to perform any movement. Particularly, the Rolandic wicket rhythm, the μ rhythm, is of the same frequency (e.g. 8-12 Hz) of visual occipital alpha waves, but from a spatially different location (posterior frontal and anterior parietal areas)[88]. Although SMR patterns presents a high inter- and intra-subjects variability regarding the signal features required to identify them, an Event Related Desynchronization/Synchronization of μ rhythm is in general consistent across subjects, regardless of the specificity of the imagined movement (i.e. what is being imagined to move).

5.2 Materials and Methods

In order to verify if ERD/ERS could be detected by this method, i.e. by automatically extracting the information from the signal plots, a BCI Simulation was performed against a public MI, Motor Imagery, dataset [76]. This dataset is composed of 8 runs for 14 participants. The first 5 runs were used for training without feedback, and the remaining 3 runs were used to test the results. The original online experiment was performed with 20 trials on each run, 10 corresponding to imagining moving the right hand and the other 10 to feet movement. This BCI simulation experiment was divided in two. In the first simulation, baseline signals, corresponding to the 1st second of each trial were compared against right hand motor imagery, 4.5 seconds ahead of the beginning of each trial. Windows of 1s length were processed for 10 trials for each of 5 runs and their descriptors extracted for both

classes. The second BCI simulation was similar but only extracting trials corresponding to feet movement imagery.

5.3 Results

For this last dataset, accuracies were calculated based on the output of the BCI simulation on the remaining 3 runs for each participant, in a single-trial approach: for each sampled window of 1s length, classification based on the NBNN algorithm was applied and a match or mismatch was obtained. Results are shown in Fig. 4 were for right-hand detection, average accuracies of around 70% were obtained for the channel C3, the best-performing channel, coincidentally with the contralateral structure of the imagined movement. On the other hand, feet imagery detection, achieved in all the channels accuracies of just above chance level.

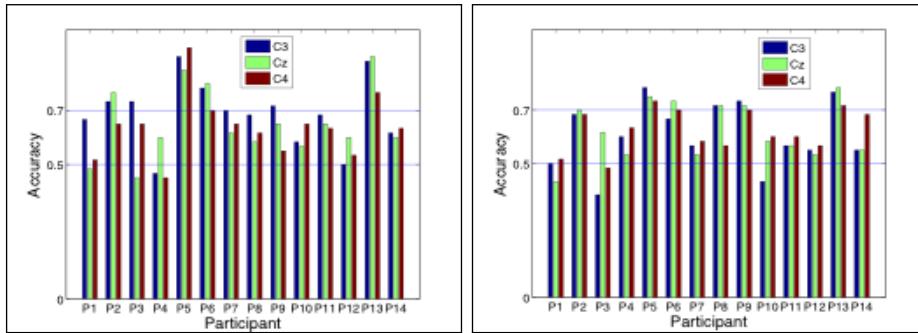


Figure 5.1: (Left) Figure 4. Classification Accuracy for discriminating windows of 1s (512 samples) of EEG for Motor Imagery detection BCI simulation (Left) Accuracy values for channels C3, Cz and C4 for the 14 participants of the described MI dataset discriminating between baseline and right-hand imagery (Right) The same procedure for feet imagery. Accuracy levels averaged to 70% were obtained only for right-hand movement on the contralateral channel C3. The SIFT descriptor size for this dataset was adjusted to 72x72 pixels.

5.4 Conclusion

Single trial asynchronous triggering of BCI can be implemented with this paradigm, particularly for right-hand motor imagery. The name μ rhythm was precisely coined because the shape of the waves have some resemblance to the greek letter (see Fig. 3). Additionally, in line with previous chapter results, the frequency of these components is exactly the same as alpha waves, 10 Hz.

Chapter 6

Event Related Potential: The P300 Wave

This can be used to do this and that
and that from Vidal paper!

Vidal

6.1 Introduction

The P300 [21, 40] is a positive deflection of the EEG signal which occurs around 300 ms after the onset of a rare and deviant stimulus that the subject is expected to attend. It is produced under the oddball paradigm [88] and it is consistent across different subjects. It has a lower amplitude ($\pm 5\mu V$) compared to basal EEG activity, reaching a Signal to Noise Ratio (SNR) of around -15 db estimated based on the amplitude of the P300 response signal divided by the standard deviation of the background EEG activity [30]. This signal can be used to implement a speller application by means of a Speller Matrix [21]. Fig. 6.1 shows an example of the Speller Matrix used in the OpenVibe open source software [66], where the flashes of rows and columns provide the deviant stimulus required to elicit this physiological response. Each time a row or a column that contains the desired letter flashes, the corresponding synchronized EEG signal should also contain the P300 signature and by detecting it, the selected letter can be identified.

In response to this counting, a potential was elicited in the brain. This response is known as a P300 wave, as first reported by Sutton. Detection of the responses and their timing in the measured signal made it possible to match the responses to one of the rows and one of the columns, and thus, the chosen symbol could be identified.

The flicker Effect (Neuro time series book) and their connection to SSVEP. Verification of the dataset by means of SSVEP detection.

6.2 Materias and Methods

6.2.1 Feature Extraction from Signal Plots

In this section, the signal preprocessing, the method for generating images from signal plots, the feature extraction procedure and the Speller Matrix identification are described. Figure 6.2 shows a scheme of the entire process.

Preprocessing Pipeline

The data obtained by the capturing device is digitalized and a multichannel EEG signal is constructed.

The 6 rows and 6 columns of the Speller Matrix are intensified providing the visual stimulus. The number of a row or column is a location. A sequence of twelve randomly permuted locations l conform an intensification sequence. The whole set of twelve intensifications is repeated k_a times.

- **Signal Enhancement:** This stage consists of the enhancement of the SNR of the P300 pattern above the level of basal EEG. The pipeline starts by applying a notch filter to the raw digital signal, a 4th degree 10 Hz lowpass Butterworth filter and finally a decimation with a Finite Impulse Response (FIR) filter of order 30 from the original sampling frequency down to 16 Hz [41].
- **Artifact Removal:** For every complete sequence of 12 intensifications of 6 rows and 6 columns, a basic artifact elimination procedure is implemented by removing the entire sequence when any signal deviates above/bellow $\pm 70\mu V$.
- **Segmentation:** For each of the 12 intensifications of one intensification sequence, a segment S_i^l of a window of t_{max} seconds of the multichannel signal is extracted, starting from the stimulus onset, corresponding to each row/column intensification l and to the intensification sequence i . As intensifications are permuted in a random order, the segments are rearranged corresponding to row flickering, labeled 1-6, whereas those corresponding to column flickering are labeled 7-12. Two of these segments should

contain the P300 ERP signature time-locked to the flashing stimulus, one for the row, and one for the column.

- **Signal Averaging:** The P300 ERP is deeply buried under basal EEG so the standard approach to identify it is by point-to-point averaging the time-locked stacked signal segments. Hence the values which are not related to, and not time-locked to the onset of the stimulus are canceled out [42].

This last step determines the operation of any P300 Speller. In order to obtain an improved signal in terms of its SNR, repetitions of the sequence of row/column intensification are necessary. And, at the same time, as long as more repetitions are needed, the ability to transfer information faster is diminished, so there is a trade-off that must be acutely determined.

The procedure to obtain the point-to-point averaged signal goes as follows:

1. Highlight randomly the rows and columns from the matrix. There is one row and one column that should match the letter selected by the subject.
2. Repeat step 1 k_a times, obtaining the $1 \leq l \leq 12$ segments $S_1^l(n, c), \dots, S_{k_a}^l(n, c)$, of the EEG signal where the variables $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$ correspond to sample points and channel, respectively. The parameter C is the number of available EEG channels whereas $n_{max} = F_s t_{max}$ is the segment length and F_s is the sampling frequency. The parameter k_a is the number of repetitions of intensifications and it is an input parameter of the algorithm.
3. Compute the Ensemble Average by

$$x^l(n, c) = \frac{1}{k_a} \sum_{i=1}^{k_a} S_i^l(n, c) \quad (6.1)$$

for $1 \leq n \leq n_{max}$ and for the channels $1 \leq c \leq C$. This provide an averaged signal $x^l(n, c)$ for the twelve locations $1 \leq l \leq 12$.

Speller Matrix letter Identification

P300 ERP Extraction Segments corresponding to row flickering are labeled 1-6, whereas those corresponding to column flickering are labeled 7-12. The extraction process has the following steps:

- **Step A:** First highlight rows and columns from the matrix in a random permutation order and obtain the Ensemble Average as detailed in steps 1, 2 and 3 in Section 6.2.1.
- **Step B:** Plot the signals $\tilde{x}^l(n, c)$, $1 \leq n \leq n_{max}$, $1 \leq c \leq C$, according Section ?? in order to generate the images $I^{(l,c)}$ for rows and columns $1 \leq l \leq 12$.
- **Step C:** Obtain the descriptors $\mathbf{d}^{(l,c)}$ for rows and columns from $I^{(l,c)}$ in accordance to the method described in Section 3.2.

Calibration A trial, as defined by the BCI2000 platform [71], is every attempt to select just one letter from the speller. A set of trials is used for calibration and once the calibration is complete it can be used to identify new letters from new trials.

During the calibration phase, two descriptors $\mathbf{d}^{(l,c)}$ are extracted for each available channel, corresponding to the locations l of a selection of one previously instructed letter from the set of calibration trials. These descriptors are the P300 templates, grouped together in a template set called T^c . The set is constructed using the steps described in Section 6.2.1 and the steps A, B and C of the P300 ERP extraction process.

Additionally, the best performing channel, bpc is identified based on the the channel where the best Character Recognition Rate is obtained.

Letter identification In order to identify the selected letter, the template set T^{bpc} is used as a database. Thus, new descriptors are computed and they are compared against the descriptors belonging to the calibration template set T^{bpc} .

- **Step D:** Match to the calibration template T^{bpc} by computing

$$\hat{row} = \arg \min_{l \in \{1, \dots, 6\}} \sum_{q \in N_T(\mathbf{d}^{(l,bpc)})} \left\| q - \mathbf{d}^{(l,bpc)} \right\|^2 \quad (6.2)$$

and

$$\hat{col} = \arg \min_{l \in \{7, \dots, 12\}} \sum_{q \in N_T(\mathbf{d}^{(l,bpc)})} \left\| q - \mathbf{d}^{(l,bpc)} \right\|^2 \quad (6.3)$$

where $N_T(\mathbf{d}^{(l,bpc)})$ is defined as $N_T(\mathbf{d}^{(l,bpc)}) = \{\mathbf{d} \in T^{bpc} / \mathbf{d} \text{ is the k-nearest neighbor of } \mathbf{d}^{(l,bpc)}\}$ for the best performing channel. This set is obtained by sorting all the elements in T^{bpc} based on distances between them and $\mathbf{d}^{(l,bpc)}$, choosing the k with

smaller values, with k a parameter of the algorithm. This procedure is based on the k-NBNN algorithm [9].

By computing the aforementioned equations, the letter of the matrix can be determined from the intersection of the row \hat{row} and column \hat{col} . Figure 6.2 shows a scheme of this process.

6.2.2 Experimental Protocol

To verify the validity of the proposed framework and method, the public dataset 008-2014 [67] published on the BNCI-Horizon website [12] by IRCCS Fondazione Santa Lucia, is used. Additionally, an own dataset with the same experimental conditions is generated. Both of them are utilized to perform an offline BCI Simulation to decode the spelled words from the provided signals.

The algorithm is implemented using VLFeat [85] Computer Vision libraries on MATLAB V2014a (Mathworks Inc., Natick, MA, USA). Furthermore, in order to enhance the impact of our paper and for a sake of reproducibility, the code of the algorithm has been made available at: <https://bitbucket.org/itba/hist>.

In the following sections the characteristics of the datasets and parameters of the identification algorithm are described.

P300 ALS Public Dataset

The experimental protocol used to generate this dataset is explained in [67] but can be summarized as follows: 8 subjects with confirmed diagnoses but on different stages of ALS disease, were recruited and accepted to perform the experiments. The Visual P300 detection task designed for this experiment consisted of spelling 7 words of 5 letters each, using the traditional P300 Speller Matrix [21]. The flashing of rows and columns provide the deviant stimulus required to elicit this physiological response. The first 3 words are used for calibration and the remaining 4 words, for testing with visual feedback. A trial is every attempt to select a letter from the speller. It is composed of signal segments corresponding to $k_a = 10$ repetitions of flashes of 6 rows and $k_a = 10$ repetitions of flashes of 6 columns of the matrix, yielding 120 repetitions. Flashing of a row or a column is performed for 0.125 s, following by a resting period (i.e. inter-stimulus interval) of the same length. After 120 repetitions an inter-trial pause is included before resuming with the following letter.

The recorded dataset was sampled at 256 Hz and it consisted of a scalp multichannel EEG signal for electrode channels Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, identified according to the 10-20 International System, for each one of the 8 subjects. The recording device was a research-oriented digital EEG device (g.Mobilab, g.Tec, Austria) and the data acquisition and stimuli delivery were handled by the BCI2000 open source software [71].

In order to assess and verify the identification of the P300 response, subjects are instructed to perform a copy-spelling task. They have to fix their attention to successive letters for copying a previously determined set of words, in contrast to a free-running operation of the speller where each user decides on its own what letter to choose.

P300 for healthy subjects

We replicate the same experiment on healthy subjects using a wireless digital EEG device (g.Nutilus, g.Tec, Austria). The experimental conditions are the same as those used for the previous dataset, as detailed in section 6.2.2. The produced dataset is available in a public online repository [64].

Participants are recruited voluntarily and the experiment is conducted anonymously in accordance with the Declaration of Helsinki published by the World Health Organization. No monetary compensation is handed out and all participants agree and sign a written informed consent. This study is approved by the *Departamento de Investigación y Doctorado, Instituto Tecnológico de Buenos Aires (ITBA)*. All healthy subjects have normal or corrected-to-normal vision and no history of neurological disorders. The experiment is performed with 8 subjects, 6 males, 2 females, 6 right-handed, 2 left-handed, average age 29.00 years, standard deviation 11.56 years, range 20-56 years.

EEG data is collected in a single recording session. Participants are seated in a comfortable chair, with their vision aligned to a computer screen located one meter in front of them. The handling and processing of the data and stimuli is conducted by the OpenVibe platform [66].

Gel-based active electrodes (g.LADYbird, g.Tec, Austria) are used on the same positions Fz, Cz, Pz, Oz, P3,P4, PO7 and PO8. Reference is set to the right ear lobe and ground is preset as the AFz position. Sampling frequency is slightly different, and is set to 250 Hz, which is the closest possible to the one used with the other dataset.

Parameters

The patch size is $X_P = 12s \times 12s$ pixels, where s is the scale of the local patch and it is an input parameter of the algorithm. The P300 event can have a span of 400 ms and its amplitude can reach $10\mu V$ [65]. Hence it is necessary to utilize a signal segment of size $t_{max} = 1$ second and a size patch X_P that could capture an entire transient event. With this purpose in consideration, the s value election is essential.

We propose the Equations 6.4 and 6.5 to compute the scale value in horizontal and vertical directions, respectively.

$$s_x = \frac{\gamma \lambda F_s}{12} \quad (6.4)$$

$$s_y = \frac{\gamma \Delta\mu V}{12} \quad (6.5)$$

where λ is the length in seconds covered by the patch, F_s is the sampling frequency of the EEG signal (downsampled to 16 Hz) and $\Delta\mu V$ corresponds to the amplitude in microvolts that can be covered by the height of the patch. The geometric structure of the patch forces a squared configuration, then we discerned that by using $s = s_x = s_y = 3$ and $\gamma = 4$, the local patch and the descriptor can identify events of $9\mu V$ of amplitude, with a span of $\lambda = 0.56$ seconds. This also determines that 1 pixel represents $\frac{1}{\gamma} = \frac{1}{4}\mu V$ on the vertical direction and $\frac{1}{F_s \gamma} = \frac{1}{64}$ seconds on the horizontal direction. The keypoints \mathbf{p}_k are located at $(x_{p_k}, y_{p_k}) = (0.55F_s \gamma, z^l(c)) = (35, z^l(c))$ for the corresponding channel c and location l (see Equation 2.11). In this way the whole transient event is captured. Figure 6.4 shows a patch of a signal plot covering the complete amplitude (vertical direction) and the complete span of the signal event (horizontal direction).

Lastly, the number of channels C is equal to 8 for both datasets, and the number of intensification sequences k_a is fixed to 10. The parameter k used to construct the set $N_T(\mathbf{d}^{(l,c)})$ is assigned to $k = 7$, which was found empirically to achieve better results. In addition, the norm used on Equations 6.2 and 6.3 is the cosine norm, and descriptors are normalized to $[-1, 1]$.

6.3 Results

Table 6.1 shows the results of applying the Histogram of Gradient Orientations (HIST) algorithm to the subjects of the public dataset of ALS patients. The percentage of correctly spelled letters is calculated while performing an offline BCI Simulation. From the seven

words for each subject, the first three are used for calibration, and the remaining four are used for testing. The best performing channel *bpc* is informed as well. The target ratio is 1 : 36; hence theoretical chance level is 2.8%. It can be observed that the best performance of the letter identification method is reached in a dissimilar channel depending on the subject being studied. Table 6.1 and 6.2 show for comparison the obtained performance rates using single-channel signals with the Support Vector Machine (SVM) [?] classifier. This method is configured to use a linear kernel. The best performing channel, where the best letter identification rate was achieved, is also depicted.

The Information Transfer Rate (ITR), or Bit Transfer Rate (BTR), in the case of reactive BCIs [88] depends on the amount of signal averaging required to transmit a valid and robust selection. Figure 6.5 shows the performance curves for varying intensification sequences for the subjects included in the dataset of ALS patients. It can be noticed that the percentage of correctly identified letters depends on the number of intensification sequences that are used to obtain the averaged signal. Moreover, when the number of intensification sequences tend to 1, which corresponds to single-intensification character recognition, the performance is reduced. As mentioned before, the SNR of the P300 obtained from only one segment of the intensification sequence is very low and the shape of its P300 component is not very well defined.

In Table 6.2 the results obtained for 8 healthy subjects are shown. It can be observed that the performance is above chance level. It was verified that HIST method has an improved performance at letter identification than SVM that process the signals on a channel by channel strategy (Wilcoxon signed-rank test, $p = 0.004$ for both datasets).

Tables 6.3 and 6.4 are presented in order to compare the performance of the HIST method versus a multichannel version of the Stepwise Linear Discriminant Analysis (SWLDA) and SVM classification algorithms for both datasets. The feature was formed by concatenating all the channels [41]. SWLDA is the methodology proposed by the ALS dataset's publisher. Since authors [67] did not report the Character Recognition Rate obtained for this dataset, we replicate their procedure and include the performance obtained with the SWLDA algorithm at letter identification. It was verified for the dataset of ALS patients that it has similar performance against other methods like SWLDA or SVM, which use a multichannel feature (Quade test with $p = 0.55$) whereas for the dataset of healthy subjects significant differences were found (Quade test with $p = 0.02$) where only the HIST method achieved a different performance than SVM (with multiple comparisons, significant difference of level 0.05).

The P300 ERP consists of two overlapping components: the P3a and P3b, the former with frontocentral distribution while the later stronger on centroparietal region [62]. Hence, the standard practice is to find the stronger response on the central channel Cz [67]. However, [41] show that the response may also arise in occipital regions. We found that by analyzing only the waveforms, occipital channels PO8 and PO7 show higher performances for some subjects.

As subjects have varying *latencies* and *amplitudes* of their P300 components, they also have a varying stability of the *shape* of the generated ERP [52]. Figure 6.6 shows 10 sample P300 templates patches for patients 8 and 3 from the dataset of ALS patients. It can be discerned that in coincidence with the performance results, the P300 signature is more clear and consistent for subject 8 (A) while for subject 3 (B) the characteristic pattern is more difficult to perceive.

Additionally, the stability of the P300 component waveform has been extensively studied in patients with ALS [73, 48, 55, 49, 51] where it was found that these patients have a stable P300 component, which were also sustained across different sessions. In line with these results we do not find evidence of a difference in terms of the performance obtained by analyzing the waveforms (HIST) for the group of patients with ALS and the healthy group of volunteers (Mann-Whitney U Test, $p = 0.46$). Particularly, the best performance is obtained for a subject from the ALS dataset for which, based on visual observation, the shape of they P300 component is consistently identified.

It is important to remark that when applied to binary images obtained from signal plots, the feature extraction method described in Section 3.2 generates sparse descriptors. Under this subspace we found that using the cosine metric yielded a significant performance improvement. On the other hand, the unary classification scheme based on the NBNN algorithm proved very beneficial for the P300 Speller Matrix. This is due to the fact that this approach solves the unbalance dataset problem which is inherent to the oddball paradigm [80].

6.4 Conclusion

Among other applications of Brain Computer Interfaces, the goal of the discipline is to provide communication assistance to people affected by neuro-degenerative diseases, who are the most likely population to benefit from BCI systems and EEG processing and analysis.

In this work, a method to extract an objective metric from the waveform of the plots of

EEG signals is presented. Its usage to implement a valid P300-Based BCI Speller application is expounded. Additionally, its validity is evaluated using a public dataset of ALS patients and an own dataset of healthy subjects.

It was verified that this method has an improved performance at letter identification than other methods that process the signals on a channel by channel strategy, and it even has a comparable performance against other methods like SWLDA or SVM, which uses a multichannel feature. Furthermore, this method has the advantage that shapes of waveforms can be analyzed in an objective way. We observed that the shape of the P300 component is more stable in occipital channels, where the performance for identifying letters is higher. We additionally verified that ALS P300 signatures are stable in comparison to those of healthy subjects.

We believe that the use of descriptors based on histogram of gradient orientation, presented in this work, can also be utilized for deriving a shape metric in the space of the P300 signals which can complement other metrics based on time-domain as those defined by [49]. It is important to notice that the analysis of waveform shapes is usually performed in a qualitative approach based on visual inspection [73], and a complementary methodology which offer a quantitative metric will be beneficial to these routinely analysis of the waveform of ERPs.

The goal of this work is to answer the question if a P300 component could be solely determined by inspecting automatically their waveforms. We conclude affirmatively, though two very important issues still remain:

First, the stability of the P300 in terms of its shape is crucial: the averaging procedure, montages, the signal to noise ratio and spatial filters all of them are non-physiological factors that affect the stability of the shape of the P300 ERP. We tested a preliminary approach to assess if the morphological shape of the P300 of the averaged signal can be stabilized by applying different alignments of the stacked segments (see Figure 6.2) and we verified that there is a better performance when a correct segment alignment is applied. We applied Dynamic Time Warping (DTW) [15] to automate the alignment procedure but we were unable to find a substantial improvement. Further work to study the stability of the shape of the P300 signature component needs to be addressed.

The second problem is the amplitude variation of the P300. We propose a solution by standardizing the signal, shown in Equation 2.16. It has the effect of normalizing the peak-to-peak amplitude, moderating its variation. It has also the advantage of reducing

noise that was not reduced by the averaging procedure. It is important to remark that the averaged signal variance depends on the number of segments used to compute it [84]. The standardizing process converts the signal to unit signal variance which makes it independent of the number k_a of signals averaged. Although this is initially an advantageous approach, the standardizing process reduces the amplitude of any significant P300 complex diminishing its automatic interpretation capability.

In our opinion, the best benefit of the presented method is that a closer collaboration of the field of BCI with physicians can be fostered [17], since this procedure intent to imitate human visual observation. Automatic classification of patterns in EEG that are specifically identified by their shapes like K-Complex, Vertex Waves, Positive Occipital Sharp Transient [28] are a prospect future work to be considered. We are currently working in unpublished material analyzing K-Complex components that could eventually provide assistance to physicians to locate these EEG patterns, specially in long recording periods, frequent in sleep research [?]. Additionally, it can be used for artifact removal which is performed on many occasions by visually inspecting signals. This is due to the fact that the descriptors are a direct representation of the shape of signal waveforms. In line with these applications, it can be used to build a database [17] of quantitative representations of waveforms and improve atlases [28], which are currently based on qualitative descriptions of signal shapes.

Table 6.1: Character recognition rates for the public dataset of ALS patients using the Histogram of Gradient (HIST) calculated from single-channel plots. Performance rates using single-channel signals with the SVM classifier are shown for comparison. The best performing channel *bp*_c for each method is visualized

Participant	<i>bp</i> _c	HIST	<i>bp</i> _c	Single Channel SVM
1	Cz	35%	Cz	15%
2	Fz	85%	PO8	25%
3	Cz	25%	Fz	5%
4	PO8	55%	Oz	5%
5	PO7	40%	P3	25%
6	PO7	60%	PO8	20%
7	PO8	80%	Fz	30%
8	PO7	95%	PO7	85%

Table 6.2: Character recognition rates for the own dataset of healthy subjects using the Histogram of Gradient (HIST) calculated from single-channel plots. Performance rates using single-channel signals with the SVM classifier are shown for comparison. The best performing channel *bpc* for each method is visualized.

Participant	<i>bpc</i>	HIST	<i>bpc</i>	Single Channel SVM
1	Oz	40%	Cz	10%
2	PO7	30%	Cz	5%
3	P4	40%	P3	10%
4	P4	45%	P4	35%
5	P4	60%	P3	10%
6	Pz	50%	P4	25%
7	PO7	70%	P3	30%
8	P4	50%	PO7	10%

Table 6.3: Character recognition rates and the best performing channel *bpc* for the public dataset of ALS patients using the Histogram of Gradient (HIST) (repeated here for comparison purposes). Performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Cz	35%	45%	40%
2	Fz	85%	30%	50%
3	Cz	25%	65%	55%
4	PO8	55%	40%	50%
5	PO7	40%	35%	45%
6	PO7	60%	35%	70%
7	PO8	80%	60%	35%
8	PO7	95%	90%	95%

Table 6.4: Character recognition rates and the best performing channel *bpc* for the own dataset of healthy subjects using the Histogram of Gradient (HIST) (repeated here for comparison purposes). Performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Oz	40%	65%	40%
2	PO7	30%	15%	10%
3	P4	40%	50%	25%
4	P4	45%	40%	20%
5	P4	60%	30%	20%
6	Pz	50%	35%	30%
7	PO7	70%	25%	30%
8	P4	50%	35%	20%



Figure 6.1: Example of the 6×6 Speller Matrix used in the study obtained from the OpenVibe software. Rows and columns flash in random permutations.

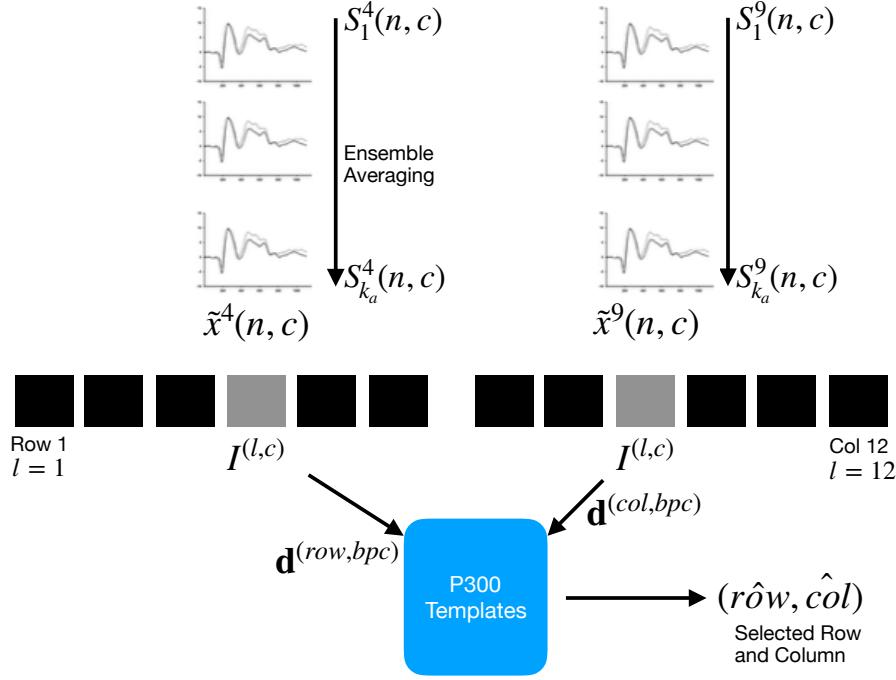


Figure 6.2: For each column and row, an averaged, standardized and scaled signal $\tilde{x}^l(n, c)$ is obtained from the segments S_i^l corresponding to the k_a intensification sequences with $1 \leq i \leq k_a$ and location l varying between 1 and 12. From the averaged signal, the image $I^{(l,c)}$ of the signal plot is generated and each descriptor is computed. By comparing each descriptor against the set of templates, the P300 ERP can be detected, and finally the desired letter from the matrix can be inferred.

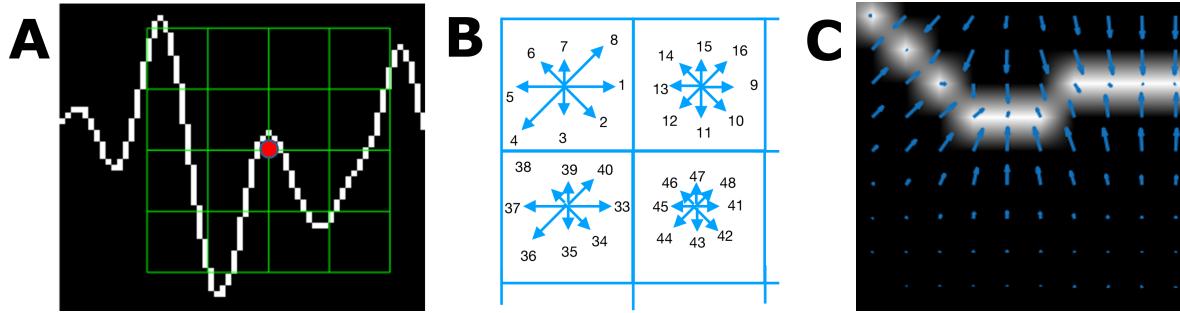


Figure 6.3: (A) Example of a plot of the signal, a keypoint and the corresponding patch. (B) A scheme of the orientation's histogram computation. Only the upper-left four blocks are visible. The first eight orientations of the first block, are labeled from 1 to 8 clockwise. The orientation of the second block $B_{1,2}$ is labeled from 9 to 16. This labeling continues left-to-right, up-down until the eight orientations for all the sixteen blocks are assigned. They form the corresponding descriptor of 128 coordinates. The length of each arrow represent the value of the histogram on each direction for each block. (C) Vector field of oriented gradients. Each pixel is assigned an orientation and magnitude calculated using finite differences.

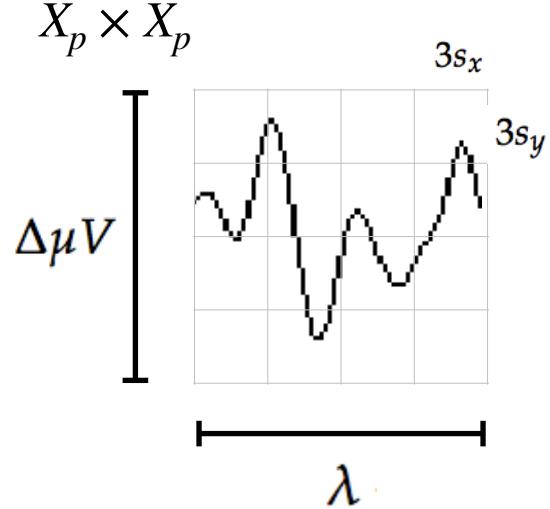


Figure 6.4: The scale of local patch is selected in order to capture the whole transient event. The size of the patch is $X_p \times X_p$ pixels. The vertical size consists of 4 blocks of size $3s_y$ pixels which is high enough as to contain the signal $\Delta\mu V$, the peak-to-peak amplitude of the transient event. The horizontal size includes 4 blocks of $3s_x$ and covers the entire duration in seconds of the transient signal event, λ .

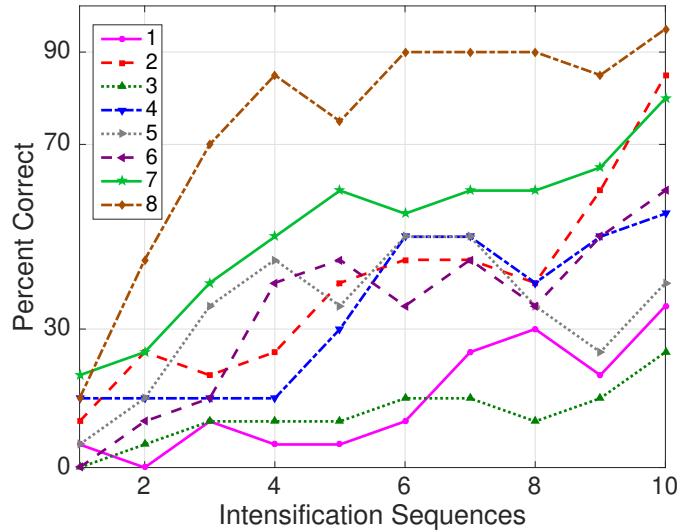


Figure 6.5: Performance curves for the eight subjects included in the dataset of ALS patients. Three out of eight subjects achieved the necessary performance to implement a valid P300 speller.

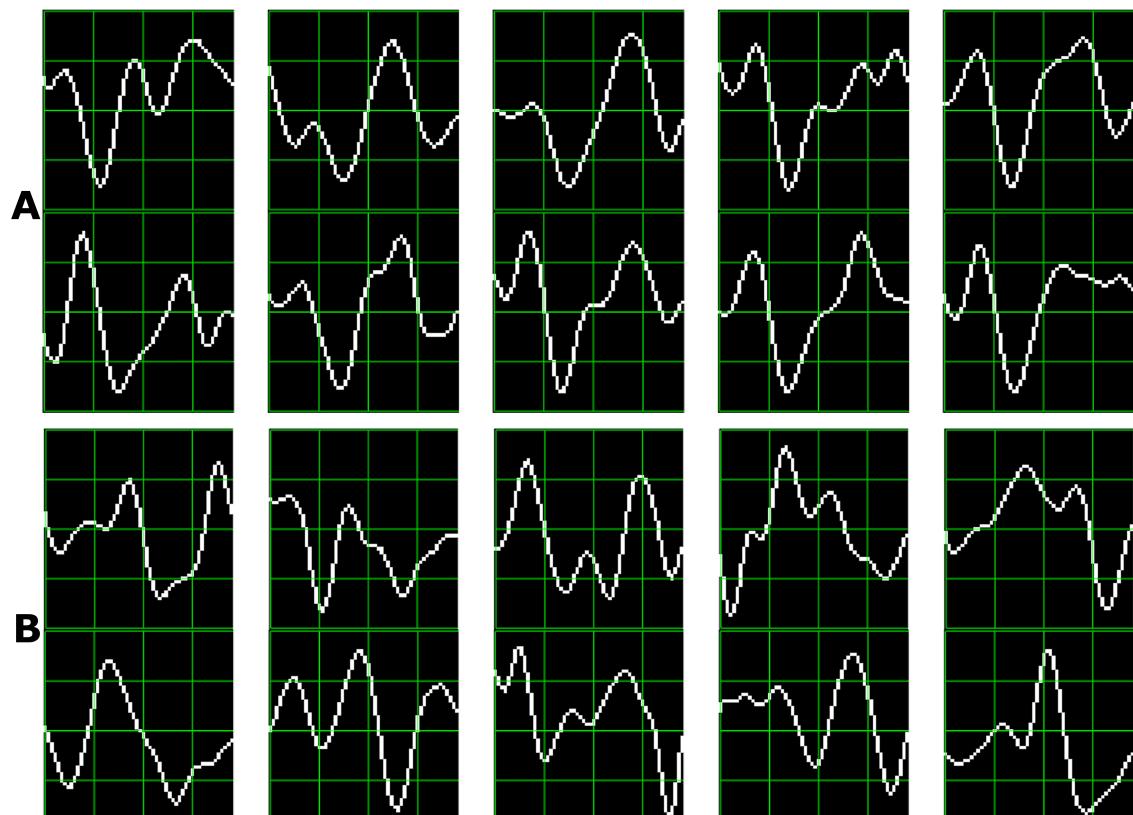


Figure 6.6: Ten sample P300 template patches for subjects 8 (A) and 3 (B) of the ALS Dataset. Downward deflection is positive polarity.

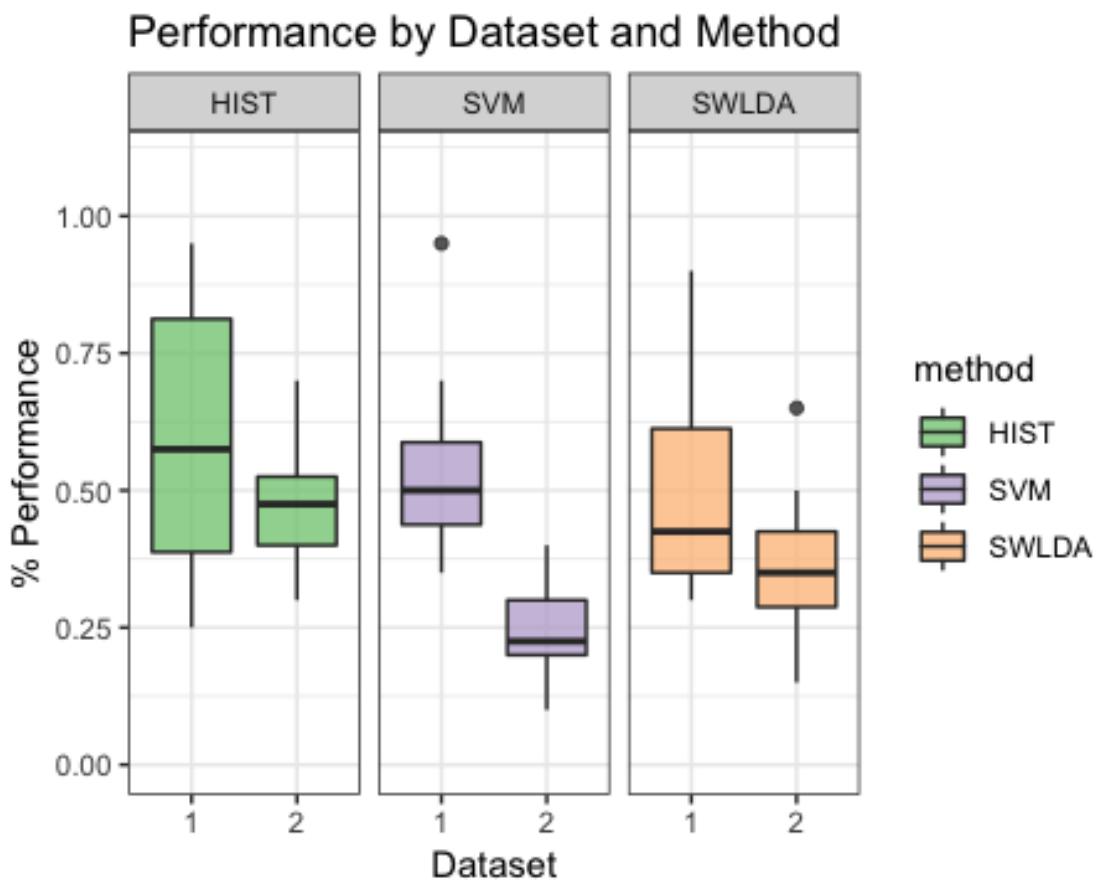


Figure 6.7: Obtained boxplots for the given algorithms.

Chapter 7

Conclusions

A method to analyze EEG signals which is based on the waveform characterization is presented. The benefits of the proposed approach are twofold, (1) it has a universal applicability because the same basic methodology can be applied to detect different patterns in EEG signals with applications to BCI and (2) it has the potential to foster close collaboration with physicians and electroencephalograph technicians because the approach follows the established procedure of the clinical EEG community of analyzing waveforms by their shapes

1. intelligible property
2. The search for meaningfull or cognitive waveforms
3. Long Term recording
4. Foster clinical interaction.

7.1 Future Work

Appendix A

BCI en Argentina

El propósito de este apéndice es ofrecer información del estado de esta disciplina en Argentina. La inevitable omisión de trabajos específicos de ninguna manera ha sido adrede, y se solicita las pertinentes disculpas. Este relevamiento fue realizado durante el transcurso del desarrollo de esta tesis, principalmente durante el primer tiempo.

Los pioneros en Argentina son los trabajos en la Universidad de La Plata, y los trabajos de la UNER.

- UNER, Faculta de Ingeniería, LIRINS,(Oro Verde) Bioingeniería Dr. Gerardo Gentilletti <http://cortex.loria.fr/Projects/STIC-AmSud-BCI>, http://www.bioingenieria.edu.ar/postgrado/index.php?option=com_content&view=category&id=72&Itemid=61 Interactive Dynamics ,Pyme Spin-off. Otros investigadores: Guerenstein, Pablo; Carolina B. Tabernig (BCI-FES system for neuro-rehabilitation of stroke patients)
- UBA, Facultad de Ingeniería, Laboratorio de Sergio Lew (<http://www.fi.uba.ar/es/node/1442>) , ”Instituto de Ingeniería Biomédicas” / Dr. Sergio Lew BCI Invasivo principalmente.
- UBA, Ingeniería Laboratorio de Sistemas Inteligentes Dr. Jorge Ierache <http://laboratorios.fi.uba.ar/lsi/>: control de robots por bioseñales, detección de emociones.
- UBA, Exactas <https://liaa.dc.uba.ar/> Applied Artificial Intelligence Lab Dr. Agustín Gravano / Dr. Diego Fernandez Slezak Tesis de grado Arneodo. Otros investigadores: Alejandro Sabatini
- INAUT, Instituto Nacional de Automática, San Juan, / Dr. Carlos Soria, Dr. Eugenio Orosco BCI Robótica (BCI híbridos, robótica asistiva) Trabajan con Teodiano Freire

Bastos en Brasil www.ncbi.nlm.nih.gov Otros investigadores: Mst. Ing. Fernando Auat Cheeín E-mail: fauat@inaut.unsj.edu.ar

- Instituto Argentino de Matemáticas Alberto Calderon / Bioing. Sergio Liberczuk, Dr. Bruno Cernuschi Frías Matemáticas y modelado del problema inverso.
- ITBA, / CiC del Dr Juan Santos, <http://www.itba.edu.ar/es/id/centros/cic-centro-de-inteligencia-computacional> Proyecto Doctorado Robótica Asistiva BCI Neurorehabilitación, Rodrigo Ramele http://www.unsam.edu.ar/tss/controlar-maquinas-con-el-pensamiento/978-3-319-13117-7_142
- UNC, Universidad Nacional de Cordoba Trabajo Final de Ingeniería: <http://www.electronicosonline.com/2013/07/08/crean-jovenes-argentinos-interface-cerebral-para-discap> Carrera de Ingeniería Biomédica: Ing. Diego Beltramone
- UNLP, LEICI / Dr. Enrique Spinelli (http://www.ing.unlp.edu.ar/leici/esp_pspinelli.html) Electrónica. Tesis de Grado de García Pablo: <http://sedici.unlp.edu.ar/handle/10915/3800631605> Tesis de Maestría de Andrea Noelia Bermudez Cicchino 31605 Cesar Caiafa (trabajó con Cichocki) <http://ccaiafa.wixsite.com/cesar>
- Universidad Nacional de Tucuman, Instituto Superior de Investigaciones Biológicas (INSIBIO) www.lamein.org Investigación sobre alternativas de codificación neural de los sistemas sensoriales. Investigadores responsables: Dr. Carmelo Felice, Mst. Ing. Fernando Farfán E-mail: cfelice@herrera.unt.edu.ar, ffarfan@herrera.unt.edu.ar
- Laboratorio de Investigación y Desarrollo en Nuevas Tecnologías (LIDeNTec) - ANSES Desarrollo de BCI Investigadores responsables: Dr. Mario Mastriani E-mail: mmastri@gmail.com
- INECO (Seguro pronto hacen BCI) Eugenia Hesse Agustín Ibañez (capo de INECO)
- IBCN Silvia Kochen http://www.ibcn.fmed.uba.ar/200_grupos-lab-epilepsia-kochen.html

Appendix B

Walkthrough BCI

Hjorth Parameters

Fractal Dimension

AR Modelling

AAR Modelling

Spatial Filtering

EEG based on Bayesian Learning

Trade-off between resolution, range and storage capacity.

range min-max Resolution Range / bitrange

Quantization noise: due to the rounding or truncation which is performed in an ADC converter.

Layers

Skin: 1mm Fat: 2 mm Skull: 7 mm Dura: 1mm CSF: 2mm Brain: 40 mm

Patients suffering from ALS degeneration of nerve cell that control voluntary muscles.

Severe cerebral palsy is a non-progressive but not unchanging, disorder of movement and posture that is the consequence of lesions or anomalies of the brain arising in the early stages of its development

MDN, Motor neuron disease actually describes a group of very similar conditions that affect motor neurons. ALS is the most common type upper motor neurons (brain spinal cord) lower motor neurons (spinal cord to muscles).

Lou Gehrig's disease in the US, MND in the UK

SCI spinal cord injury less than 5 percent recover locomotion

Brain Stem stroke fatal can derive in locked-in state.

bci for assistive technologies book

Appendix C

SIFT

The history of Scale Space tracks back to Witkin 1983, where it was applied to time series. He highlighted the Spatial Coincidental assumption. Basically, the number of zero crossing of the first derivative is reduced with increasing scale.

Biomimetic Applications

This method is actually composed on two submethods: the first is the keypoint localization, while the second is the histogram of gradient orientations, which is the basis for this thesis.

bla bla bla

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