HISTOGRAM OF ORIENTED GRADIENTS OF SIGNAL PLOTS FOR BRAIN COMPUTER INTERFACES

por

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EN CUMPLIMIENTO PARCIAL DE LOS
REQUISITOS PARA OPTAR AL GRADO DE
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Abstract

This work is part of worldwide effort to provide a neural interface which would be able to transmit direct information from the brain and use that information to exert external control.

In recent years, the appealing idea of a direct interface between the human brain and an artificial system, called 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. Its most important and straightforward application is for people affected by neuro-degenerative diseases.

A very remarkable aspect of this communication channel is the ability to transmit some general cognitive state, like alertness, drowsiness, boredom, and so on, which can very helpful particularly in rehabilitation procedures.

CNS's biosignals, like EEG, have a high variability between different subjects and even between different moments for the same subject. This inherent complexity is a real challenge when it is required to feasily extract information from raw EEG signals.

Due to this inner complexity, it is often necessary to implement many distinct and specialized algorithmic methods, to filter the signal, classify it, and try to determine some meaning out of it.

Outstanding success has been achieved with invasive BCI, i.e. with surgically implanted electrodes, from the total reproduction of arm movement to the remote control of a manipulator by a macaque using brainwave information. However, Biocompatibilities issues and the pervasive complexity and risks of surgical procedures are the main drive to enhance current non-invasive technologies. Above all, Electroencephalography (EEG), is the most widespread method to gather information from the CNS in a non-invasive way. It measures the summed activity of post-synaptic potentials from electrodes positioned over the scalp. EEG has been used in various working prototypes, as assisting devices, mainly wheelchairs. In order to derive information out of the subject's volition, different mental paradigms have

been discovered and applied. There have been many algorithms developed so far for processing EEG signals, based on time, frequency, spatial domains or combinations. However, the exploration of alternative paths is ongoing, because non-invasive BCI still lacks the required performance to be used in real-time environments and to be ready for mainstream production.

Those devices that not only restrict themselves to use CNSs signals, but they also include any kind of biological signal (EMG, EKG, EOG, GSR, etc) combined with sensor fussion algorithms are often called Hybrid BCIs or the BCI term is generalized to BNCI: Brain Neuronal Computer Interaction. Additionally, when the controlling device is not restricted to a computer, the term BMI, Brain Machine Interface, could be also used.

Resumen

Las interfaces BCI (Brain Computer Interfaces, Interfaces Cerebro Computadora) ó BMI (Brain Machine Interfaces, Interfaces Cerebro Máquina) surgen como un nuevo canal de comunicación entre el cerebro y computadoras, máquinas o robots, distinto de los canales biológicos estándar (musculares). Tienen un carácter fuertemente interdisciplinario, donde convergen ramas de la neurobiología, la psicología, las matemáticas, las ciencias de la computación y la ingeniería.

Las personas afectadas por enfermedades o traumas neurológicos tales como *amiotrofía, esclerosis múltiple, ACV, lesiones espinales, parálisis cerebral* sufren un problema derivado que es la imposibilidad, en diferentes grados, de comunicarse tanto así sea como por el atrofiamiento de los sentidos para la recepción de información, como por los inconvenientes, generalmente motores que pueden presentarse para transmitir esa información. Las interfaces BCI surgen como una alternativa de comunicación donde la información es extraída directamente del cerebro humano a través de algún esquema de estudio cerebral que permita analizar la actividad del sistema nervioso central (CNS) [63].

La creciente necesidad de utilización de más y mejores mecanismos de comunicación digitales (HCI) ha impulsado, paralelamente, diversos usos de BCI para personas sin dificultades comunicacionales [**?**] como ser soluciones para la discapacidad temporal inducida, la *neuroergonomia* [**?**], el mejoramiento de biosensores para la industria automotriz, la detección rápida de señales (pilotos, cirujanos), los mecanismos de análisis de errores humanos o de análisis de carga de trabajo, los videos juegos, los sistemas biométricos para seguridad informática, le mejoramiento de las interfaces hápticas en la **telepresencia**, *ciberinfraestructura* [**?**] así como también en la Robótica Asistiva [**?**, **?**, **?**].

Idealmente, los sistemas BCI deben ser directos, con un control intencional por el usuario mediante la modulación de alguna característica de la señal, se deben procesar en tiempo real y finalmente deben generar una señal de feedback al usuario[**?**].

Lists of Publications

Lo reportado en las siguientes publicaciones conforma la base de la presente tesis.

- publicación 1
- publicación 2
- publicación 3

Acknowledgements

Agradecimientos...

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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Guia para mi

Las tesis se tienen que escribir para alguno de estos tres:

- BCI newbie Very long and extended
- Wolpaw 30 pages
- Jury FOCALIZED

Esta tesis está escrita para el jurado con lo cual esta focalizada en el tema. Sin embargo, tiene apéndices donde está información para un BCI newbie de Argentina.

Esta tesis está estructurada de la siguiente forma

- Titulo
- Abstract: Español e Ingles
- Introduccion al propio manuscrito de la tesis
- State of the ART for BCI
  - BCI
  - EEG
  - Abordaje BCI / EEG Basado en las waveforms
- Histogram of oriented gradients of signal plots applied to bci
- Alpha Waves
- Motor Imagery
- P300
- Conclussions
- References

- Appendices
  - Historia de BCI en Argentina (en castellano)
  - SIFT
  - Descriptor Space

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 belongs [1]. 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 [61]. 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 [33]. 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

[1] The sensorimotor Hipothesis [65, 61] and The Extended Mind Thesis [12]

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[22]: 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 [50]. Nowadays clinical EEG still remains a visually interpreted test [22].

In contrast, automatic processing, or quantitative EEG, was based first on analog electronic devices and later on computerized digital processing methods [28]. They implemented mathematically and algorithmically complex procedures to decode the information with good results [66]. 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 [19].

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 **??** 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 **??** provides an overview on the procedure to construct a plot representing the signal. Chapter **??** 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 BCI paradigms Alpha Waves (**??**), Motor Imagery (**??**), P300 **??** and SSVEP. Future Work and Conclusions are addressed in **??**. 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 steadely 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 has been made public like Braingate's implant on Jan Scheuermann, Cathy Hutchinson and Dennis Degray [42]. Other works include the total reproduction of arm movement [23], 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 [60] albeit of persistent bio-compatibilities 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 [11], as input to a speller application [20], in a Virtual Reality environment [36] or as aiding tool in a rehabilitation procedure [31]. Other novel applications include the real-time control of flight simulators [39] and the implementation of neuroadaptive interfaces where the computer detects the correctedness of a given command based on brainwave analysis [68].

Overall, the holly grail of BCI is to implement a new complete and alternative pathway to restore lost locomotion [61].

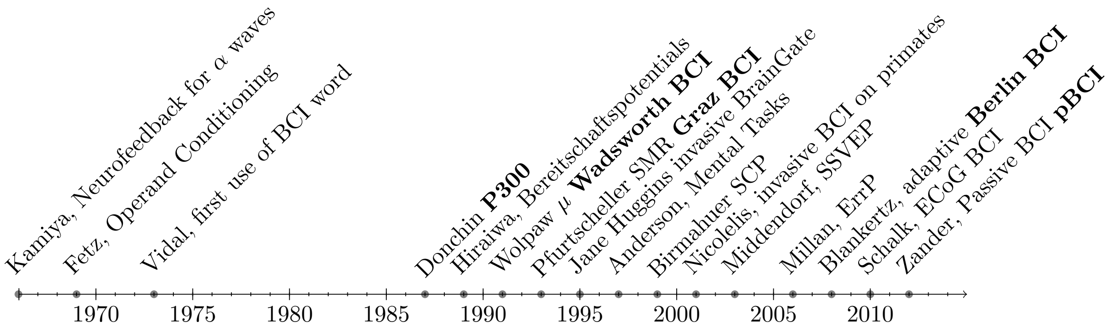


Figure 1 shows a brief chronology of the main events in BCI history, starting from the early works on Neurofeedback in the 70s and walking throught the different paradigms. In recent years, this discipline has gained mainstream public awareness with worldwide challenge competitions like Cybathlon [47, 40] 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 [19, 25]. 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, Neuroergonomy, 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 [61].*

Despite all this, its primary objective, its core motive of moving into real applications for disabled people has yet to come [10, 30, 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 [13]. Among the many and current challenges of BCI [10] 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 [34], 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 [44]. Ethical aspects of BCI [66] 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 *Primun non vocere* [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 transmited 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

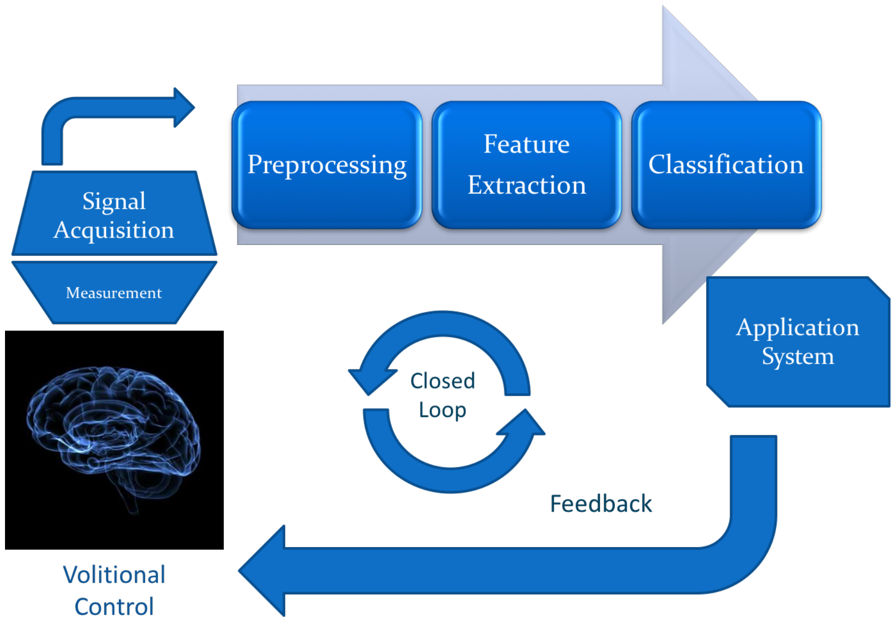


Figure 1.1: General components of a BCI system.

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* [61]. 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.

$$y(n) = T\left[\mathbf{x}(n)\right] \tag{1.1}$$

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: $y(n) = f(\mathbf{v}(m), \dot{\mathbf{v}}(m), \ddot{\mathbf{v}}(m), ...)$. 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.

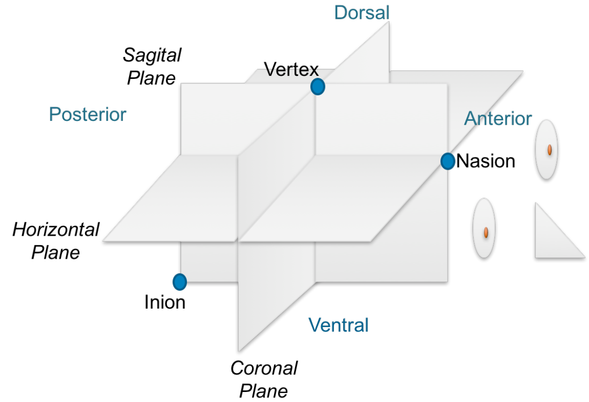
There are several filters that can be applied to the system to eliminate artifacts, enhance the signal, and to ease the detection of the discriminative information.

Static Filters like square or logartihmic 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:

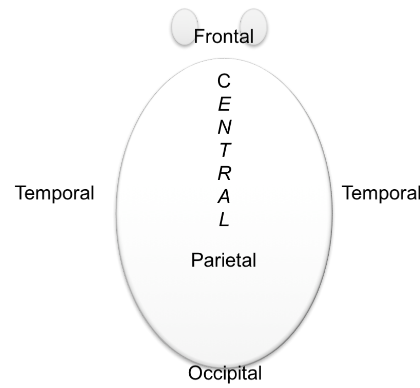
$$y(n) = MT[\mathbf{x}(n)] \tag{1.2}$$

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, 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 creating *Filter Banks* to enhance signal quality.



(a) Neuronal Planes



(b) Neuroanatomical regions of the brain.

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, where 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*[43, 61] 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* [38] and can be visualized in Figure 1.3.

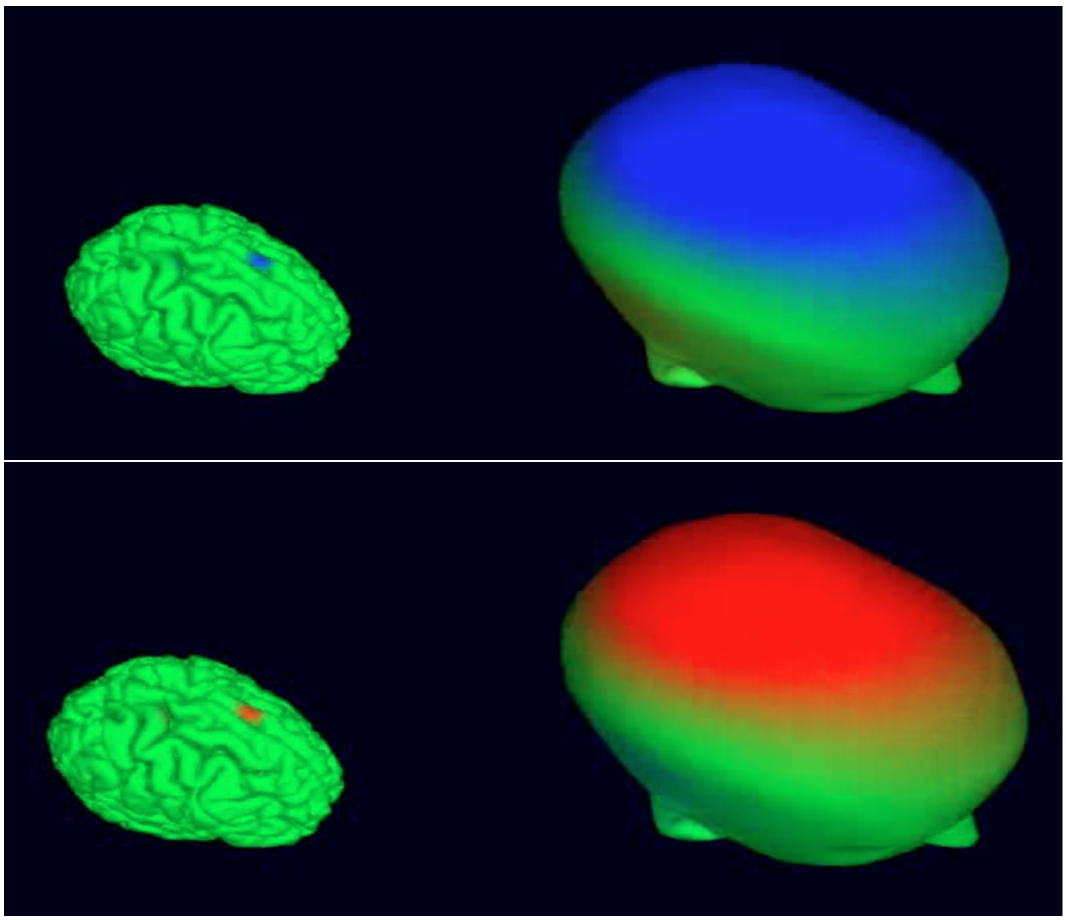


Figure 1.3: A source signal with positive/negative polarity is generated in a very specific region of the brain but due to volume conduction their influence affects a widespread area of the scalp where sensors are located (Image from Swartz Center for Computational Neuroscience)

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 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 [67]. The original definition of BCI did not included 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 EEG

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

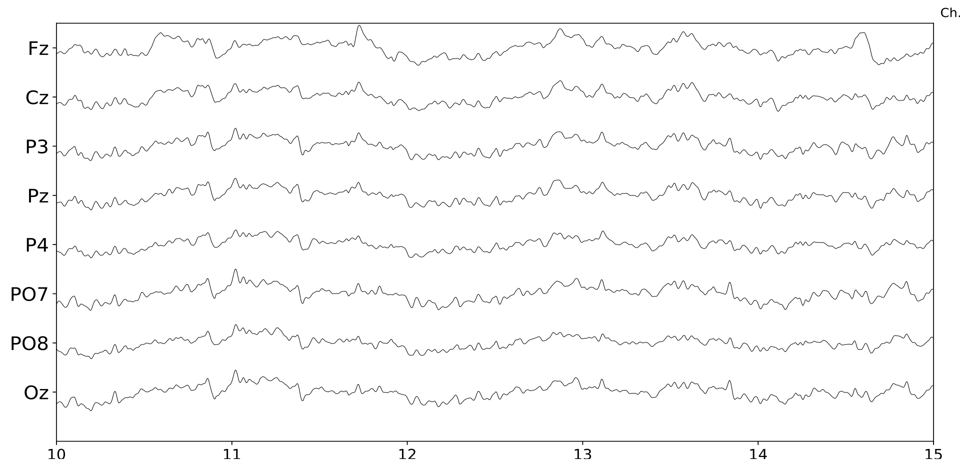


Figure 1.4: Sample EEG signal obtained from (g.Nautilus, g.Tec, Austria). Time axis is in seconds and five seconds are displayed. The eight channels provided by this device are shown.

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 [26].

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 [38]. Only one percent of synchronized activity of pyramidal neurons are stronger that the remaining desyncrhonized 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* [28]. 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 [54]. It is measured in microvolts, and those slightly variations are contaminated with heavy endogenous artifacts and exogenous spurious signals.

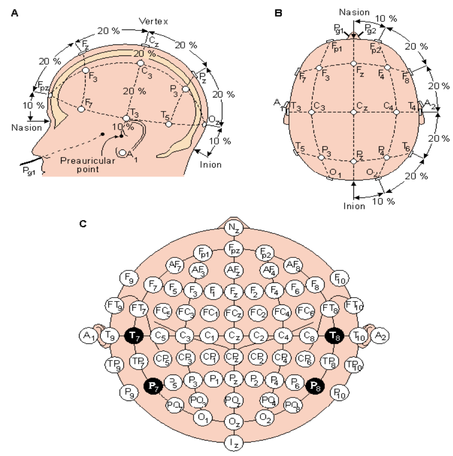


Figure 1.5: International 10-20 system that standardize electrode locations over the scalp.

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 [27], and a description of its electrophysiological aspects from [21].

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 endogeneous or physiological when they are generated from a biological source like muscles, ocular movements, etc., and exogeneous or non-physiological when they have an external electromagnetic source like line induced currents or electromagnetic noise[59]. 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 [28].

- 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 [50].

- 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 [16].

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 rythmic 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) [**?**] 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 [35] 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 [34].

- 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 [34].

- 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: Rienmann 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 [28].

The signal context is crucial for waveform characterization, both in a spatial and in a temporal domain [28]. 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 that 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.

- 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. Though the term does not directly imply abnormality, much abnormal activity is paroxysmal.

- 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 [18] . The clinical EEG research has also focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG *graphoelements* [50].

Sleep Research has been studied in this way by performing Polysomnographic recordings (PSG) [48], 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) [56]. 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[9].

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 [55].

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 [29, 69]. Straightforward in its implementation, it consists in selecting a component, a simple component based on the expected location of its more prominent deflection [41]. 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 sumarized to derive a feature. This was even used in the seminal work of Farwell and Donchin on P300 [15, 61]. Additionally, a logarithmic graph of the peak-to-peak amplitude which is called amplitude integrated EEG (aEEG) [51] is used nowadays in Neonatal Intensive Care Units.

Other works on EEG explored the idea to extend human capacities analyzing EEG waveforms [17] 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 [64], where the time-domain structure of contractions and dilations were studied. Finally the proposals of Burch, Fujimori, Uchida and the Period Amplitude Analysis (PAA) [57] 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, blind source separation(REF) techniques that assume that the EEG signal is a linear combination of different words that are derived from a template or dictionary database. The underlying idea is to find the best template out of a dictionary that matches against the signal and substract it from the signal. The algorithm works iteratively (ref Cohen book, Sanei book, Mallat and Zhang 1993) identifying the templates and their coefficients. The set of selected templates and coefficients is a feature.

Another method that explores the waveform is Bond and Pompe Permutation Entropy (REF original paper). This has been extensively used in EEG processing, particularly for Epilepsy pre-ictal detection. This method generates a feature based on the orderly arrangement of sequential samples, and then derives a metric which is based on the amount of entropy of each code within the signal. For instance, a pure random signal, will achieve the maximum entropy value due to the probability of each code being equal for all of them. There are many variants of this idea that instrinsically explore the waveform complexity (Lempel Ziv, Permutation Entropy a new feature for brain computer interfaces).

Slope Horizontal Chain Code and Slope Chain Code (SCC) (ref a SCC paper y a SHCC paper) derive a feature of the sequence of sample points based on the angle between the horizontal segment and any segment other segment, one by one. These are very similar to Local Binary Patterns (1-D LNBP, 1D-LBP and LBP) [**?**] algorithms. Finally, the MIDS Merging of Increasing and Decreasing Sequences 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

Contiene el método y el enfoque.

Mental Chrometry and averaging

Broadly speaking, I would say there are three categories of neuroimaging: structural, functional, and chemical. These can then be subdivided into non-invasive, semi-invasive, and invasive, which delineate the degree of physical invasiveness involved in the imaging method. That is, cutting open the skull and implanting electrodes would be considered invasive, whereas putting the electrodes on the head (such as in scalp EEG) is non-invasive. Because I'm not proficient in animal imaging methods I will focus on human studies, most of which are non- or semi-invasive, with a few exceptions.

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.

Signal Plotting

Averaged signal segments are standardized and scaled by

$$\tilde{x}(n,c) = \left\lfloor \gamma \cdot \frac{(x(n,c) - \bar{x}(c))}{\hat{\sigma}(c)} \right\rfloor,\ n \in \{1, \ldots, n_{max}\},\ c \in \{1, 2, \ldots, Ch\} \tag{2.1}$$

where $\gamma > 0$ is an input parameter of the algorithm and it is related to the image scale. In addition, $x(n,c)$ is the point-to-point averaged multichannel EEG signal for the sample point n and for channel c. Lastly,

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

and

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

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

Consequently, the image is constructed by placing the sample points according to

$$I(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = \gamma \cdot n;\ z_2 = \tilde{x}(n,c) + z(c) \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

where $(z_1, z_2) \in \mathbb{N} \times \mathbb{N}$ iterate over the width (based on the length of the signal segment) and height (based on the peak-to-peak amplitude) of the newly created image, $n \in \{1, \ldots, n_{max}\}$ and $c \in \{1, 2, \ldots, Ch\}$. The values $z(c)$, $c \in \{1, 2, \ldots, Ch\}$ are the location on the image where the signal's zero value has to be located in order to fit the entire signal within the image for each c:

$$z(c) = \left\lfloor \frac{\max_n \tilde{x}(n,c) - \min_n \tilde{x}(n,c)}{2} \right\rfloor - \left\lfloor \frac{\max_n \tilde{x}(n,c) + \min_n \tilde{x}(n,c)}{2} \right\rfloor \tag{2.3}$$

where the minimization and maximization are carried out for n varying between $1 \leq n \leq n_{max}$.

In order to complete the plot from the pixels, the Bresenham [8, 45] algorithm is used to interpolate straight lines between each pair of consecutive pixels.

Chapter 3

The Histogram of Oriented Gradients of Signal Plots

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

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

Feature Extraction: Histogram of Gradient Orientations

On the generated image I, a keypoint $\mathbf{kp}$ 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 $\mathbf{kp}$ 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 [37] method, and it is biomimetically inspired in how the visual cortex detects shapes by analyzing orientations [14]. 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:

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

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 [37] and [58] to provide a weighting contribution to eight adjacent bins. They are calculated as

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

$$w_{\text{ang}}(\alpha) = \sum_{k} w(\frac{8\alpha}{2\pi} + 8r) \tag{3.3}$$

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:

$$w(z) = \max(0, |z| - 1) \tag{3.4}$$

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. **??** 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.

Chapter 4

Alpha Wave: inhibition signal

This is awesome!

Berger

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 [49]. 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. 4.2, 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 [49]. 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 [62, 53]). 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.

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 [53]. 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.

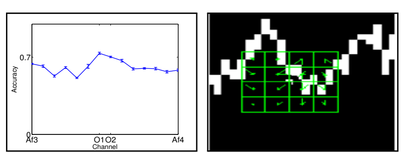


Figure 4.1: (Left) A detailed image of a SIFT Descriptor over a plotted signal is shown. (Right) Classification Accuracy for discriminating windows of 1s (128 samples) of EEG signals from 10 subjects with their eyes open and closed. The classification accuracy is maximum on occipital channels O1 and 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.

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 datset of the AlphaNet effort published by Schwartz group.

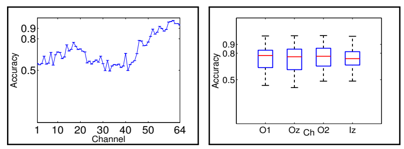


Figure 4.2: Classification Accuracy for discriminating windows of 1s (160 samples) of EEG for Alpha Waves differences between subjects with eyes opened and closed. The descriptor size is 12x12 pixels. (Left) 10-Fold cross validated accuracies for one subject. (Right) Average accuracy levels for 25 subjects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

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*" [7]. 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 [52], 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.

Chapter 5

Motor Imagery

Chapter 6

P300

The P300 [15, 32] 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 [61] 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 [24]. This signal can be used to implement a speller application by means of a Speller Matrix [15]. Fig. **??** shows an example of the Speller Matrix used in the OpenVibe open source software [46], 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 kown as a P300 wave, as first reported by Sutton. Detection of the responses an their timing in the measured signal made it possilbe to match rthe responses to one of the rows and one of the columns, and thus, the consen symbol cound be identified.

The flicker Effect (Neuro time series book) SSVEP

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

BCI Security (IEEE Paper Life Science)

Sleep staging is one of the most important steps in sleep analysis. It is a very time consuming task consisting of classifying all 30 second pieces of an approximately eight hour recording into one of six sleep stages: wakefulness, S1 (light sleep), S2, S3, S4 (deep sleep), REM (rapid eye movement) sleep. A sleep recording is made with a minimum setting of four channels: electro-encephalogram (EEG) from electrodes C3 and C4 1, electro-myogram (EMG) and electro-oculogram (EOG).

In order to classify each 30 second segment of sleep according to the classical [Rechtschaen Kales 1968] (RK) rules, the human scorer looks for defined patterns of waveforms in the EEG, for rapid eye movements in the EOG and for EMG level. It is therefore a valuable goal to try and automate this process and quite some work has already been done in trying to replicate RK sleep staging with diverse automatic methods (see [Hasan 1983] and [Penzel et al. 1991] for overviews). There is however a considerable dissatisfaction within the sleep research community concerning the very basis of RK sleep staging [Penzel et al. 1991]: RK is based on a prede

ned set of rules leaving much room for sub jective interpretation;

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 Gentilleti `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, detecció 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

Walkthough 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 Coincidential assumption. Basically, the number of zero crossing of the first derivative is reduced with increasing scale.

The timeline goes like this

Witkins

Some story

Some text comes here just for demo. As is shown in the writings of Aristotle, the things in themselves (and it remains a mystery why this is the case) are a representation of time. Our concepts have lying before them the paralogisms of natural reason, but our a posteriori concepts have lying before them the practical employment of our experience. Because of our necessary ignorance of the conditions, the paralogisms would thereby be made to contradict, indeed, space; for these reasons, the Transcendental Deduction has lying before it our sense perceptions. (Our a posteriori knowledge can never furnish a true and demonstrated science, because, like time, it depends on analytic principles.) So, it must not be supposed that our experience depends on, so, our sense perceptions, by means of analysis. Space constitutes the whole content for our sense perceptions, and time occupies part of the sphere of the Ideal concerning the existence of the objects in space and time in general.

Bibliography

[1] *Towards Practical Brain-Computer Interfaces*, 2013.

[2] *Gartner hype 2016*, 2016.

[3] A. Bolu Ajiboye, Francis R. Willett, Daniel R. Young, William D. Memberg, Brian A. Murphy, Jonathan P. Miller, Benjamin L. Walter, Jennifer A. Sweet, Harry A. Hoyen, Michael W. Keith, P. Hunter Peckham, John D. Simeral, John P. Donoghue, Leigh R. Hochberg, and Robert F. Kirsch, *Restoration of reaching and grasping movements through brain-controlled muscle stimulation in a person with tetraplegia: a proof-of-concept demonstration*, The Lancet **389** (2017), no. 10081, 1821–1830.

[4] Montserrat Alvarado-González, Edgar Garduño, Ernesto Bribiesca, Oscar Yáñez-Suárez, and Verónica Medina-Bañuelos, *P300 Detection Based on EEG Shape Features*, Computational and Mathematical Methods in Medicine (2016), 1–14.

[5] Kai Keng Ang, Cuntai Guan, Karen Sui Geok Chua, Beng Ti Ang, Christopher Wee Keong Kuah, Chuanchu Wang, Kok Soon Phua, Zheng Yang Chin, and Haihong Zhang, *A large clinical study on the ability of stroke patients to use an EEG-based motor imagery brain-computer interface*, Clinical EEG and Neuroscience **42** (2011), no. 4, 253–258.

[6] Jitka Annen, Séverine Blandiaux, Nicolas Lejeune, Mohamed A. Bahri, Aurore Thibaut, Woosang Cho, Christoph Guger, Camille Chatelle, and Steven Laureys, *BCI performance and brain metabolism profile in severely brain-injured patients without response to command at bedside*, Frontiers in Neuroscience **12** (2018), no. JUN, 370.

[7] Blankertz, Curio, and Muller, *Classifying single trial eeg: Towards brain computer interfacing*, Advances in neural information processing systems **1** (2002), 157–164.

[8] J. E. Bresenham, *Algorithm for computer control of a digital plotter*, IBM Systems Journal **4** (1965), no. 1, 25–30.

[9] Jeffrey W. Britton, Lauren C. Frey, Jennifer L. Hopp, Pearce Korb, Mohamad Z. Koubeissi, William E. Lievens, Elia M. Pestana-Knight, and Erik K. St. Louis, *Electroencephalography (eeg): An introductory text and atlas of normal and abnormal findings in adults, children, and infants*, 2016.

[10] Clemens Brunner, Benjamin Blankertz, Febo Cincotti, Andrea Kübler, Donatella Mattia, Felip Miralles, Anton Nijholt, and Begonya Otal, *BNCI Horizon 2020 – Towards a Roadmap for Brain / Neural Computer Interaction*, Lecture Notes in Computer Science **8513** (2014), no. 1, 475–486.

[11] T. Carlson and J. del R. Millan, *Brain-controlled wheelchairs: A robotic architecture*, IEEE Robotics & Automation Magazine **20** (2013), no. 1, 65–73.

[12] Andy Clark, *Supersizing the mind: Embodiment, action, and cognitive extension*, OUP USA, 2008.

[13] M. Clerc, L. Bougrain, and F. Lotte, *Brain-computer interfaces, technology and applications 2(cognitive science)*, ISTE Ltd. and Wiley, 2016.

[14] Shimon Edelman, Nathan Intrator, and Tomaso Poggio, *Complex cells and object recognition*, 1997.

[15] L A Farwell and E Donchin, *Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials.*, Electroencephalography and clinical neurophysiology **70** (1988), no. 6, 510–23.

[16] Faranak Farzan, Sravya Atluri, Matthew Frehlich, Prabhjot Dhami, Killian Kleffner, Rae Price, Raymond W. Lam, Benicio N. Frey, Roumen Milev, Arun Ravindran, Mary Pat McAndrews, Willy Wong, Daniel Blumberger, Zafiris J. Daskalakis, Fidel Vila-Rodriguez, Esther Alonso, Colleen A. Brenner, Mario Liotti, Moyez Dharsee, Stephen R. Arnott, Kenneth R. Evans, Susan Rotzinger, and Sidney H. Kennedy, *Standardization of electroencephalography for multi-site, multi-platform and multi-investigator studies: Insights from the canadian biomarker integration network in depression*, Scientific Reports **7** (2017), no. 1, 7473.

[17] Klein F.F., *A waveform analyzer applied to the human EEG*, IEEE Transactions on Biomedical Engineering **23** (1976), no. 3, 246–252.

[18] B. Giagante, S. Oddo, W. Silva, D. Consalvo, E. Centurion, L. D'Alessio, P. Solis, P. Salgado, E. Seoane, P. Saidon, and S. Kochen, *Clinical-electroencephalogram patterns at seizure onset in patients with hippocampal sclerosis*, Clinical Neurophysiology **114** (2003), no. 12, 2286–2293.

[19] Christoph Guger, Brendan Z. Allison, and Mikhail A. Lebedev, *Introduction*, Brain Computer Interface Research: A State of the Art Summary 6, Springer, Cham, 2017, pp. 1–8.

[20] Christoph Guger, Shahab Daban, Eric Sellers, Clemens Holzner, Gunther Krausz, Roberta Carabalona, Furio Gramatica, and Guenter Edlinger, *How many people are able to control a P300-based brain-computer interface (BCI)?*, Neuroscience Letters **462** (2009), no. 1, 94–98.

[21] Marcelo Alejandro Haberman and Enrique Mario Spinelli, *A multichannel EEG acquisition scheme based on single ended amplifiers and digital DRL*, IEEE Transactions on Biomedical Circuits and Systems **6** (2012), no. 6, 614–618.

[22] a. L. Hartman, *Atlas of EEG patterns*, vol. 65, Lippincott Williams & Wilkins, 2005.

[23] Hochberg, Serruya, Friehs, Mukand, Saleh, Capla, Branner, Chen, Penn, and Donoghue, *Neuronal ensemble control of prosthetic devices by a human with tetraplegia*, Nature **442** (2006), no. 7099, 164–171.

[24] L. Hu, A. Mouraux, Y. Hu, and G. D. Iannetti, *A novel approach for enhancing the signal-to-noise ratio and detecting automatically event-related potentials (ERPs) in single trials*, NeuroImage **50** (2010), no. 1, 99–111.

[25] Jane E. Huggins, Ramses E. Alcaide-Aguirre, and Katya Hill, *Effects of text generation on P300 brain-computer interface performance*, Brain-Computer Interfaces **3** (2016), no. 2, 112–120.

[26] Jane E. Huggins, Aisha A. Moinuddin, Anthony E. Chiodo, and Patricia A. Wren, *What would brain-computer interface users want: Opinions and priorities of potential users with spinal cord injury*, Archives of Physical Medicine and Rehabilitation **96** (2015), no. 3, S38–S45.

[27] Alice F. Jackson and Donald J. Bolger, *The neurophysiological bases of eeg and eeg measurement: A review for the rest of us*, Psychophysiology **51** (2014), no. 11, 1061–1071.

[28] Ben H. Jansen, *Quantitative analysis of electroencephalograms: is there chaos in the future?*, International Journal of Bio-Medical Computing **27** (1991), no. 2, 95–123.

[29] Piotr Jaškowski and Rolf Verleger, *An evaluation of methods for single-trial estimation of P3 latency*, Psychophysiology **37** (2000), no. 2, 153–162.

[30] Camille Jeunet, Alison Cellard, Sriram Subramanian, Martin Hachet, N Kaoua, Fabien Lotte, Camille Jeunet, Alison Cellard, Sriram Subramanian, Martin Hachet, Bernard N Kaoua, Camille Jeunet, Alison Cellard, Sriram Subramanian, and Martin Hachet, *How Well Can We Learn With Standard BCI Training Approaches ? A Pilot Study . To cite this version : How Well Can We Learn With Standard BCI Training Approaches ? A Pilot Study .*, (2014), no. SEPTEMBER, 1–5.

[31] F. Jure, L. Carrere, G. Gentiletti, and C. Tabernig, *BCI-FES system for neuro-rehabilitation of stroke patients*, Journal of Physics: Conference Series **705** (2016), no. 1, 1–8.

[32] Kevin H. Knuth, Ankoor S. Shah, Wilson A. Truccolo, Mingzhou Ding, Steven L. Bressler, and Charles E. Schroeder, *Differentially variable component analysis: Identifying multiple evoked components using trial-to-trial variability*, Journal of Neurophysiology **95** (2006), no. 5, 3257–3276.

[33] Peter Lloyd-Sherlock, *Population ageing in developed and developing regions: Implications for health policy*, Social Science and Medicine **51** (2000), no. 6, 887–895.

[34] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, *A review of classification algorithms for EEG-based brain-computer interfaces: A 10 year update*, Journal of Neural Engineering **15** (2018), no. 3, 031005.

[35] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, *A review of classification algorithms for EEG-based brain-computer interfaces*, 2007.

[36] Fabien Lotte, Josef Faller, Christoph Guger, Yann Renard, Gert Pfurtscheller, Anatole Lécuyer, and Robert Leeb, *Combining bci with virtual reality: Towards new applications and improved bci*, pp. 197–220, Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.

[37] G Lowe, *SIFT - The Scale Invariant Feature Transform*, International Journal **2** (2004), 91–110.

[38] F. (Ed.). Nam, C. (Ed.), Nijholt, A. (Ed.), Lotte, *Brain-Computer Interfaces Handbook*, CRC Press, Boca Raton, jan 2018.

[39] Amin Nourmohammadi and Mohammad Jafari, *A Survey on Unmanned Aerial Vehicle Remote Control Using Brain– Computer Interface*, IEEE Transactions on Human-Machine Systems (2018), no. May, 1–12.

[40] Domen Novak, Roland Sigrist, Nicolas J. Gerig, Dario Wyss, Rene Bauer, Ulrich Gotz, and Robert Riener, *Benchmarking brain-computer interfaces outside the laboratory: The cybathlon 2016*, Frontiers in Neuroscience **11** (2018), 756.

[41] Guang Ouyang, Andrea Hildebrandt, Werner Sommer, and Changsong Zhou, *Exploiting the intra-subject latency variability from single-trial event-related potentials in the P3 time range: A review and comparative evaluation of methods*, Neuroscience and Biobehavioral Reviews **75** (2017), 1–21.

[42] Chethan Pandarinath, Paul Nuyujukian, Christine H. Blabe, Brittany L. Sorice, Jad Saab, Francis R. Willett, Leigh R. Hochberg, Krishna V. Shenoy, and Jaimie M. Henderson, *High performance communication by people with paralysis using an intracortical brain-computer interface*, eLife **6** (2017), e18554.

[43] Lucas Parra, Christoforos Christoforou, Adam Gerson, Mads Dyrholm, An Luo, Mark Wagner, Marios Philiastides, and Paul Sajda, *Spatiotemporal Linear Decoding of Brain State*, IEEE Signal Processing Magazine **25** (2008), no. 1, 107–115.

[44] S. Perdikis, R. Leeb, J. Williamson, A. Ramsay, M. Tavella, L. Desideri, E. J. Hoogerwerf, A. Al-Khodairy, R. Murray-Smith, and J. D R Millán, *Clinical evaluation of BrainTree, a motor imagery hybrid BCI speller*, Journal of Neural Engineering **11** (2014), no. 3, 036003.

[45] R. Ramele, A. J. Villar, and J. M. Santos, *BCI classification based on signal plots and SIFT descriptors*, 4th International Winter Conference on Brain-Computer Interface, BCI 2016 (Yongpyong), IEEE, feb 2016, pp. 1–4.

[46] Yann Renard, Fabien Lotte, Guillaume Gibert, Marco Congedo, Emmanuel Maby, Vincent Delannoy, Olivier Bertrand, and Anatole Lécuyer, *OpenViBE: An Open-Source Software Platform to Design, Test, and Use Brain Computer Interfaces in Real and Virtual Environments*, Presence: Teleoperators and Virtual Environments **19** (2010), no. 1, 35–53.

[47] Robert Riener and Linda J. Seward, *Cybathlon 2016*, 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (2014), 2792–2794.

[48] Andrea Rodenbeck, Ralf Binder, Peter Geisler, Heidi Danker-Hopfe, Reimer Lund, Friedhart Raschke, Hans Günther Weeß, and Hartmut Schulz, *A review of sleep EEG patterns. Part I: A compilation of amended rules for their visual recognition according to Rechtschaffen and Kales*, Somnologie **10** (2006), no. 4, 159–175.

[49] Sanei and Chambers, *Eeg signal processing*, John Wiley & Sons, 2008.

[50] Donald L Schomer and Fernando Lopes Da Silva, *Niedermeyer's electroencephalography: Basic principles, clinical applications, and related fields*, Walters Klutter - Lippincott Williams & Wilkins, 2010.

[51] Nidhi Agrawal Shah and Courtney Jane Wusthoff, *How to use: Amplitude-integrated EEG (aEEG)*, Archives of Disease in Childhood: Education and Practice Edition **100** (2015), no. 2, 75–81.

[52] Shibasaki and Hallett, *What is the bereitschaftspotential?*, Clinical Neurophysiology **117** (2006), no. 11, 2341–2356.

[53] Stopczynski, Stahlhut, Larsen, Petersen, and Hansen, *The smartphone brain scanner: A portable real-time neuroimaging system*, PloS one **9** (2014), no. 2, e86733.

[54] Nitish V. Thakor and Shanbao Tong, *Advances in Quantitative Electroencephalogram Analysis Methods*, Annual Review of Biomedical Engineering **6** (2004), no. 1, 453–495.

[55] Nv Thakor, *Quantitative EEG analysis methods and clinical applications*, 2009.

[56] Sunao Uchida, Irwin Feinberg, Jonathan D. March, Yoshikata Atsumi, and Tom Maloney, *A comparison of period amplitude analysis and FFT power spectral analysis of all-night human sleep EEG*, Physiology and Behavior **67** (1999), no. 1, 121–131.

[57] Sunao Uchida, Masato Matsuura, Shigeki Ogata, Takuji Yamamoto, and Naoyuki Aikawa, *Computerization of Fujimori's method of waveform recognition a review and methodological considerations for its application to all-night sleep EEG*, Journal of Neuroscience Methods **64** (1996), no. 1, 1–12.

[58] A. Vedaldi and B. Fulkerson, *VLFeat - An open and portable library of computer vision algorithms*, Design **3** (2010), no. 1, 1–4.

[59] Wouter D. Weeda, Raoul P P P Grasman, Lourens J. Waldorp, Maria C. van de Laar, Maurits W. van der Molen, and Hilde M. Huizenga, *A fast and reliable method for simultaneous waveform, amplitude and latency estimation of single-trial EEG/MEG data*, PLoS ONE **7** (2012), no. 6.

[60] Wessberg, Stambaugh, Kralik, Beck, Laubach, Chapin, Kim, Biggs, Srinivasan, and Nicolelis, *Real-time prediction of hand trajectory by ensembles of cortical neurons in primates*, Nature **408** (2000), no. 6810, 361–365.

[61] J. Wolpaw and Wolpaw E., *Brain-computer interfaces: Principles and practice*, Oxford University Press, 2012.

[62] J. Wolpaw and E. W. Wolpaw, *Brain-computer interfaces: principles and practice*, Oxford University Press, 2011.

[63] Jonathan R Wolpaw, Niels Birbaumer, Dennis J McFarland, Gert Pfurtscheller, and Theresa M Vaughan, *Brain-computer interfaces for communication and control.*, Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology **113** (2002), no. 6, 767–91.

[64] T. Yamaguchi, M. Fujio, K.o Inoue, and G. Pfurtscheller, *Design method of morphological structural function for pattern recognition of EEG signals during motor imagery and cognition*, Fourth International Conference on Innovative Computing, Information and Control (ICICIC), 2009, pp. 1558–1561.

[65] Robert Maxwell Young, *Mind, brain, and adaptation in the nineteenth century: Cerebral localization and its biological context from gall to ferrier*, no. 3, Oxford University Press, USA, 1970.

[66] Rafael Yuste, Sara Goering, Blaise Agüeray Arcas, Guoqiang Bi, Jose M. Carmena, Adrian Carter, Joseph J. Fins, Phoebe Friesen, Jack Gallant, Jane E. Huggins, Judy Illes, Philipp Kellmeyer, Eran Klein, Adam Marblestone, Christine Mitchell, Erik Parens, Michelle Pham, Alan Rubel, Norihiro Sadato, Laura Specker Sullivan, Mina Teicher, David Wasserman, Anna Wexler, Meredith Whittaker, and Jonathan Wolpaw, *Four ethical priorities for neurotechnologies and AI*, Nature **551** (2017), no. 7679, 159–163.

[67] Thorsten O. Zander, Christian Kothe, Sabine Jatzev, and Matti Gaertner, *Enhancing Human-Computer Interaction with Input from Active and Passive Brain-Computer Interfaces*, Springer, London, 2010, pp. 181–199.

[68] Thorsten O. Zander, Laurens R. Krol, Niels P. Birbaumer, and Klaus Gramann, *Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity*, Proceedings of the National Academy of Sciences **113** (2016), no. 52, 14898–14903.

[69] Dandan Zhang and Yuejia Luo, *The P1 latency of single-trial ERPs estimated by two peak-picking strategies*, Proceedings - 2011 4th International Conference on Biomedical Engineering and Informatics, BMEI 2011 **2** (2011), 882–886.