HISTOGRAM OF ORIENTED GRADIENTS OF SIGNAL PLOTS FOR BRAIN COMPUTER INTERFACES

por

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EN CUMPLIMIENTO PARCIAL DE LOS
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Contents

Abstract

This work is part of worldwide effort to provide a neural interaface 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) [**?**].

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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0.1 Como estructurar esta tesis

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 [3]. 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 [2]. 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. *Neuroscience is the new black* and that is why this is the **third** motive. 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 provide neurofeedback. The **fifth**, final and

[1] The sensorimotor Hipothesis [4, 3] and The Extended Mind Thesis [1]

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

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

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.

0.1.1 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.

0.1.2 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

State of the Art

Where are the waveforms ? By estimates from the 2016 BCI Award, around 71.2% of noninvasive BCI research is based on Electroencephalography (EEG) [1]. Although mature clinical EEG has traditionally focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG graphoelements [2], signal analysis methods which follow this path has been overshadow in BCI research. Few works have investigated the idea of exploiting signal waveforms to analyze the EEG signal on BCI applications. The seminal work of Bandt-Pompe Permutation Entropy [3] explores succinctly this concept and in [4] an approach based on Slope Horizontal Chain Code is presented. A similar methodology is implemented in [5] based on Mathematical Morphological Analysis. The work proposed here is based on waveform analysis of the shape of the EEG signal, but using the histogram of gradient orientations, mimicking what traditionally electroencephalographers have been doing for almost a century: visually inspecting raw EEG signal plots. Material, Methods and Results: The histogram of gradient orientations is a popular and powerful tool used in Computer Vision to characterize local features from images and is the basis of the feature generation algorithm in Lowe's SIFT Descriptor [7]. This technique can be applied to identify components in EEG signals 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 the newly created image depending on the physiological phenomena under study and finally (5) calculation of the histogram of gradient orientations using finite differences from the image around the keypoint (Figure 1). This method generates a feature, a normalized 128-dimension SIFT descriptor, which can be used to compare the signal segments that were used to generate the plots, thus they can be used to analyze the underlying cognitive phenomena. This method was used to identify and detect Visual Occipital Alpha Waves, Motor Imagery Rolandinc

Mu rhythms [6] with results above chance level. It was also tested on P300 detection for Visual P300 Speller Matrix on ALS public dataset and for an own dataset of healthy subjects as well as identifying K-Complexes in sleep EEG (unpublished, under review). Discussion: A procedure which is biomimetically based on how the visual cortex works by detecting orientations, ironically, is used precisely to detect information from the brain. Although we found that it is possible to decode with accuracy above chance level and to differentiate patterns with cognitive correlations, the stability of the signature of the component is a key and challenging aspect. The method was also applied to patterns which are more frequently studied by their spectral characteristics. Significance: 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.

Esta sección contiene el estado del arte del método

BCI + EEG

Cómo es el abordaje basado en Waveforms

Machine Learning

Shearlets

Scalar Space Theory

Diffusion Tensor Imagin

La idea es estructurar el paso a paso de como se puede ir usando el descriptor de gradientes de sift para mapear informacion. Primero con una señal cruda, luego agregarle informacion extra, luego agregar ruido al azar, y finalmente empezar con información real de señales. El tema luego se focaliza en EEG especificamente para BCI.

Describir la importancia de la impedencia (basado en el libro de Signal processing for neuro) con el paper que habla sobre EEG mas la pagina 144 del libro 2 de lotte.

Aca tambien pueden ir las referencias a la tesis de spinelli

Pattern Matching

Esta es la razon porque el metodo funciona ya que lo que termina detectando es de manera masiva esas formas especificas que son las que le dan a las ondas alfa y mu sus nombres.

In human electrophysiology, oscillations with stereotyped nonsinusoidal shapes include the sensorimotor mu rhythm, motor cortical beta oscillation, and cortical slow oscillations. The mu rhythm oscillates at an alpha frequency (around 10 Hz) and was named because its waveform shape resembles the Greek character m (Figure 1A). It is characterized by the fact that one extremum (e.g., its peak) is consistently sharper than the other (e.g., its trough); it is also described as an arch, comb, or wicket shape [4–10]. In addition to the sensorimotor mu rhythm, we have recently highlighted that motor cortical beta oscillations also have striking nonsinusoidal features [11]. These beta oscillations manifest a sawtooth shape in that their voltage either rapidly rises before more slowly falling off, or vice versa (Figure 1B).

1.1 EEG

The EEG signal goes from 10-100 microvolts

monopolar, reference, averaged, bipolar

segmentation is commong, which is generally called epoching trials are general realizations of the experiment. tampering window could be gaussian, hamming, blackman, hanning

Impedance

1.2 BCI

A key contribution to this expansion has been the field of Brain Computer Interfaces (BCI) [3] which is the pursuit of the development of a new channel of communication particularly aimed to persons affected by neurodegenerative diseases.

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 [**?**], as input to a speller application [**?**], in a Virtual Reality environment [**?**] or as aiding tool in a rehabilitation procedure [**?**]. The holly grail of BCI is to implement a new complete and alternative pathway to restore lost locomotion [3].

EEG signals are remarkably complex and have been characterized as a multichannel non-stationary stochastic process. Additionally, they have high variability between different subjects and even between different moments for the same subject, requiring adaptive and co-adaptive calibration and learning procedures [?]. Hence, this imposes an outstanding challenge that is necessary to overcome in order to extract information from raw EEG signals.

Moreover, EEG markers [?] that can be used to transmit volitional information are limited, and each one of them has a particular combination of appropriate methods to decode them. Inevitably, it is necessary to implement distinct and specialized algorithmic methods, to filter the signal, enhance its Signal to Noise Ratio (SNR), and try to determine some meaning out of it.

BCI has gained mainstream public awareness with worldwide challenge competitions like Cybathlon [?] and even been broadcasted during the inauguration ceremony of the 2014 Soccer World Cup. New developments have overcome the out-of-the-lab high-bar and they are starting to be used in real world environments [?, ?]. However, 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 [?].

—

Where are we. BCI plateau

BCNI Horizon, what the people is saying

Status in Argentina

Reference to thesis

OpenBCI and the Wearables movement

Neuro....everythig

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 [**?**, **?**] 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 [**?**] method, and it is biomimetically inspired in how the visual cortex detects shapes by analyzing orientations [**?**]. 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:

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

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

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

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

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. **??** 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 [?]. 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. 4.3, 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 [?]. 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 [?, ?]). 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.

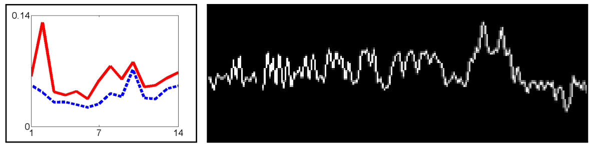

Figure 4.1: PSD values for every channel (x-axis) are being shown for class 1, dashed line, and class 2, solid line, for Dataset I (left). Sample EEG plot image corresponding to the subject 1 (center) for class 1 (eyes open), for the channel 7 (O_1)

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 [?]. 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.

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

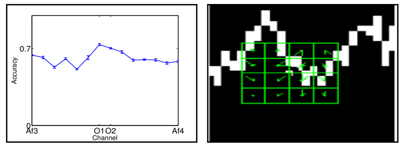

Figure 4.2: (Left) A detailed image of a SIFT Descriptor over a plotted signal is shown. (Right) Classification Accuracy for discriminating windows of 1s (128 samples) of EEG signals from 10 subjects with their eyes open and closed. The classification accuracy is maximum on occipital channels O1 and O2. The descriptor size is 12x12 pixels which corresponds to a variation of 12 microvolts in the signal amplitude during 0.09 s

detect fairly some BCI components.

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

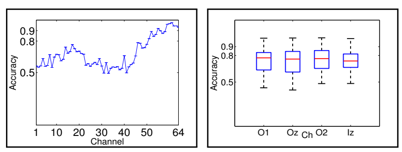

Figure 4.3: Classification Accuracy for discriminating windows of 1s (160 samples) of EEG for Alpha Waves differences between subjects with eyes opened and closed. The descriptor size is 12x12 pixels. (Left) 10-Fold cross validated accuracies for one subject. (Right) Average accuracy levels for 25 subjects 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*" [**?**]. 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 [**?**], 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

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

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.

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[3] Wolpaw Elizabeth Wolpaw, Jonathan R, *Brain-Computer Interfaces: Principles and Practice*, Oxford University Press, 2012.

[4] 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.