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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DEPARTAMENTO DE DOCTORADO

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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.

Abstract

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. La interfaz BCI surge 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* [**?**], mejoramiento de sensores para la industria automotriz, detección rápida de señales (pilotos, cirujanos), ERN (corrección de errores), videos juegos, interfaces confidenciales (seguridad), telepresencia (mejoramiento de interfaces hápticas), *ciberinfraestructura* [**?**] y particularmente una contribución relevante en la Robótica Asistiva [**?**, **?**, **?**].

Los sistemas BCI deben ser Directos, con un control intencional por el usuario de alguna característica de la señal, deben procesar en tiempo real y finalmente 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

List of Tables

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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

During the last years of the 20th century an emerging idea took form and shaped one of the oldest dreams of mankind.

In terms of Schwartz Laboratory, the bandwidth of communication based on HCI devices seems very low (cite)

As mentioned in the most cited paper of the discipline, there are three motives behind BCI: the first is the Aging Societies: estimated for 2025, 800 millions people will be over 65 years old, and 2/3 of them on developing countries. This may lead to an increased tendency to develop diseases that affect motor pathways, that will require some for of assistance from technology. At the same time, science has provided the understanding that an Active Lifestyle is necessary to maintain body and mind health. It is known that the ability to walk independently is a key indicator of psychological and physical health. Last, but not least, the digital world demands more methods of interactions. Digital society demands more mechanisms to interpret our surrounding world and to translate our intentions through digital gadgets.

Objectives of this work

This thesis tries to unravel the following question: it is possible to analyze and discriminate brainwaves signals, particularly Electroencephalographic signals, out of the automatic processing of the shape of waveforms using the Histogram of oriented gradients ?

To do that, I ask the reader to join me following this path: (1) we will give details of what is Brain Computer Interfaces and the particularities of the first window of electric mind: the EEG. (2) we will cover also the state of the art in the methods that explore the waveform automatically. The following section will give an overview about how a digital plotting is actually performed. The following section is the core of this theses and we will describe the Histogram of Gradient Orientations and how it can be used to process one dimensional signals. Next, results and experimental procedures will be described, particularly Alpha Waves (4.3), Motor Imagery (5.2), P300 (6) and SSVEP. Future Work and Conclussions will be addressed in 66.5. Additionally, appendixes provide extra more information which is not extrictly related to this thesis but which provides information regarding the state-of-the-art of this discipline in Argentina, and also provides more inforamtion about the SIFT method and the theory behind the Histogram of Gradient Orientations of Signal Plots.

Chapter 1

Visually Decoding Brain Signals

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) [**?**] 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 [?].

EEG signals are remarkably complex and have been characterized as a multi-channel 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

Signal Plots

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.

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

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.

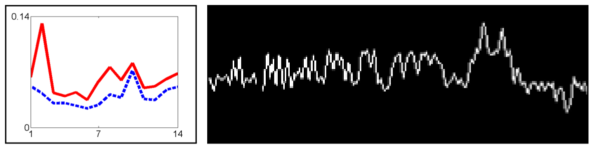

Figure 4.1: PSD values for every channel (x-axis) are being shown for class 1, dashed line, and class 2, solid line, for Dataset I (left). Sample EEG plot image corresponding to the subject 1 (center) for class 1 (eyes open), for the channel 7 (O_1)

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

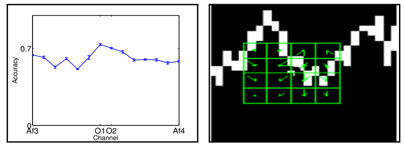

Figure 4.2: (Left) A detailed image of a SIFT Descriptor over a plotted signal is shown. (Right) Classification Accuracy for discriminating windows of 1s (128 samples) of EEG signals from 10 subjects with their eyes open and closed. The classification accuracy is maximum on occipital channels O1 and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

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.

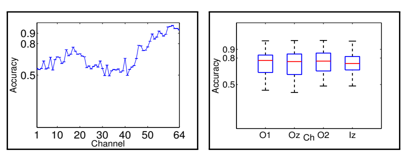

Figure 4.3: Classification Accuracy for discriminating windows of 1s (160 samples) of EEG for Alpha Waves differences between subjects with eyes opened and closed. The descriptor size is 12x12 pixels. (Left) 10-Fold cross validated accuracies for one subject. (Right) Average accuracy levels for 25 subjects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

Chapter 8

Legal and Ethical Implications

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).

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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-e 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-p 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.