Computational Intelligence Techniques for Electro-Physiological Data Analysis

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Accronyms

AD	Alzheimer's Disease
ADHD	Attention Deficit Hyperactivity Disorder
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANS	Autonomic Nervous System
AR	Autoregression
BCI	Brain Computer Interface
BD	Bipolar Disorder
BL	Baseline
BSM	Body Surface Mapping
CB	Cognitive-Behavioral
CC	Cluster Coefficient
CH	Channel
CI	Computer Intelligence
CO	Coherence
EC	European Community
EAG	Electroantennography
EC	Eyes Closed
ECG	Electrocardiography
ECoG	Electrocorticography
EEG	Electroencephalography
EER	Equal Error Rate
EMG	Electromyography
EO	Eyes Open
EOG	Electrooculography
ERG	Electroretinography
ERP	Evoked Related Potential
FAR	False Acceptance Rate
FB	Frequency Band
FDA	Fisher Discriminant Analysis
FF	Fitness Function
FFT	Fast Fourier Transform
fMRI	Functional Magnetic Resonance Imaging

Table 1: Acronyms

FPE	First Psychotic Episode
FV	Fitness Value
GA	Genetic Algorithm
HCI	Human Computer Interface
KI	Connectivity Index
LFP	Local Field Potential
LVQ	Learning Vector Quantisation
MCI	Mild Cognitive Impairment
MDD	Major Depressive Disorder
MIST	Montreal Imaging Stress Task
ML	Machine Learning
MMN	Miss-Match Negativity
MRI	Magnetic Resonance Imaging
NN	Neural Network
PL	Path Length
PET	Positron Emission Topography
PMR	Progressive Muscle Relaxation
PTSD	Post-Traumatic Stress Disorder
SA	Sino-Atrial
SL	Synchronization Likelihood
SP	Signal Processing
STREP	Specific Targeted Research Project
SVM	Support Vector Machines
SZ	Schizophrenia / Schizophrenic
TAR	True Acceptance Rate
TM	Transcendental Meditation
UB	University of Barcelona
VCG	Vector Cardiogram
VR	Virtual Reality
vs	Versus

Table 2: Acronyms continuation

Chapter 1

Introduction

1.1 Introduction

This work contains the efforts I have made in the last years in the field of Electrophysiological data analysis. Most of the work has been done at Starlab Barcelona S.L. and part of it at the Neurodinamics Laboratory (Faculty of Psychology) of the Department of Psychiatry and Clinical Psychobiology of the University of Barcelona (UB).

The main work deals with the analysis of Electroencephalographic (EEG) signals, although other signals have also been used. Several data sets have been collected and analysed applying advanced Signal Processing (SP) techniques. On a later stage Computational Intelligence (CI) techniques, such as Machine Learning (ML) and Genetic algorithms (GA), have been applied, mainly to classify the different conditions from the EEG data sets. As it will be explained in corresponding sections, 3 applications involving EEG and classification are proposed. Each one of these applications corresponds to each one of the 3 case studies presented in this thesis:

- Analysis of electrophysiological signals for biometric purposes (chapter 3).
- EEG differences in First Psychotic Episode (FPE) Patients (chapter 4).
- Markers of stress in the EEG signal (chapter 5).

Each one of these researches are described at their corresponding chapters (3, 4 and 5 respectively). The next sections of this chapter (1.2, 1.3 and 1.4) provide a general introduction of this thesis and explain the interest of applying CI techniques to Electrophysiological data Analysis, which is the main motivation of this work. A review of the current techniques and the different fields of application are explained in these sections. The specific objectives of this thesis are listed in chapter 2. The general discussion of this work can be found in chapter 6 and finally the conclusion can be found in chapter 7.

All the publications I have been involved in during this research can be found in annexes B, C, D, E, F and G. In annex A we can find a list along with a short description of the different projects I have worked during these years of research. Finally in annex H we can find a summary of this thesis in Spanish.

1.2 Computational Intelligence

Inside the field of Artificial Intelligence (AI), we find an emerging approach called Computational Intelligence (CI). It relies on heuristic algorithms such as fuzzy systems, Artificial Neural Networks (ANN), Genetic Algorithms (GA) and Evolutionary Computation. Other techniques used by CI are Swarm Intelligence, Fractals, Chaos Theory, Artificial Immune Systems, etc... In many cases the tools from CI are inspired by natural behaviour such as how neurones transmit information from one to another (as is the case in the creation of the ANN), the behaviour of a flock of birds (Swarm Intelligence), or the evolution and genetic rules such as mutation, cross-over and generations (GA). A nice review of these different techniques can be found in (Engelbrecht [1]).

CI combines elements of learning, adaptation, evolution and Fuzzy logic to create programs that are, in some sense, intelligent. CI research does not reject statistical methods, but often gives a complementary view (as is the case with fuzzy systems). ANN, for instance, is a branch of CI that is closely related to Machine Learning (ML). CI is further closely associated with soft computing, connectionist systems and cybernetics. The main purpose of CI is to address complex real world problems where other more traditional techniques, such as probabilistic and statistical methods, are ineffective. As an example of such a real world problem, which is in fact one of the central aspects of this thesis, is how to extract and find optimal features from EEG signals that are useful for detecting differences between a healthy control from a schizophrenic patient, for instance.

The pattern recognition and classification are a central problem of CI, in particular of the ML subfield (see Bishop [2]). Several techniques are used in order to perform these tasks, such as Fisher Discriminant Analysis (FDA), ANN, Support Vector Machines (SVM), etc.... In the case of the research presented in this work, I have used different classifiers to label unknown data, based on a prior learning (i.e. training) of the classifier done with a given training data set. Several categories of ML techniques exist and they can be classified depending on if the learning is performed with a given training data set with labelled data (Supervised Learning) or if the training set has no labels (Unsupervised learning or cluster analysis). There are other categories such as semi-supervised learning, where the data set contains both labeled and unlabelled data. On this research I used only supervised learning classifiers.

In Figure 1.1, we can see a scheme of the main steps I applied to analyse the different datasets of this thesis. The first step is to collect the Physiological data by means of an EEG amplifier. The next step is to pre-process the data. This step often includes re-referencing the signals, the application of filters to have a cleaner signal, a visualisation of the data to discard noisy signals and to check if the signals are meaningful. The feature extraction step is applied after the pre-processing. At this point, we look for interesting features in the signals to be used in the next stages. The next two steps can include Computational Techniques. For instance, in the feature selection step (also called dimensionality reduction), if we have extracted a large number of features, usually we want to select the more suited feature for our purposes. In order to do so, several techniques can be applied, such as GA. Finally the last step 'classification' often includes ML techniques and classifiers.

A very complete review of the different methods used in the steps previously explained can be found in (Bashashati et al. [3]). This survey focus on signal processing algorithms used in

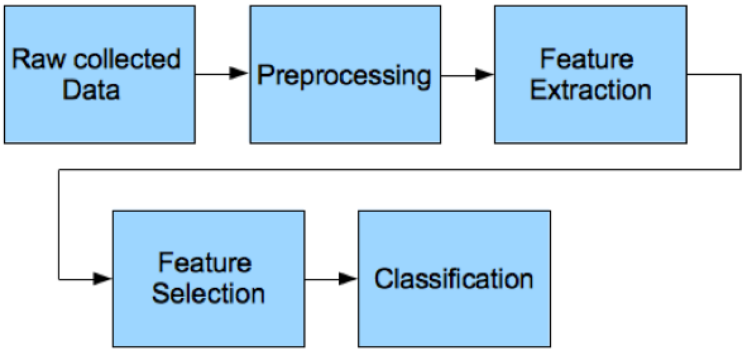

Figure 1.1: Scheme of the main steps applied to the data analysis

Brain Computer Interfaces (BCI). These types of systems are able to provide a direct communication channel from the brain to different actuators, such as spelling devices or wheelchair control, overpassing the traditional communication systems such as voice or keystroking. The different steps needed to build a BCI are very similar to the ones described in the previous paragraph. One of the major differences is the real time requirement often needed to control a BCI. In any case, the work of (Bashashati et al. [3]) deeply explains the different methods and signal processing algorithms used in the different steps, such as pre-processing, feature extraction, feature selection and classification methods. It also includes a further step called post-processing, which in few words, corrects the parameters of the previous steps by analysing the output of the classification. This extra step is not used in our work.

Also in the book "Introduction to machine learning for brain imaging" by (Lemm et al. [4]) we can find a deep review of the most common used machine learning and pattern recognition techniques used in EEG data analysis. From this work, we see that linear classifiers, such as FDA, are the more used. Actually, theory suggests that, under proper circumstances, FDA would be the optimal classifier. This fact supports the use of such classifiers in most of the works presented in this thesis.

1.3 Signal Processing

Since Electrophysiological signals are in general complex signals with a lot of 'hidden' features, a visual inspection is usually not a proper approach to extract useful information from them. That is why Signal Processing (SP) techniques are virtually always applied to analyse Electrophysiological signals. Furthermore, since computers have become a widely used tool for scientists, the use of SP techniques is even more common nowadays.

SP is a branch of mathematics which deals with the analysis of signals with the objective to extract information out of them, mainly the underlying mechanism that generates the signal under study. Signals are often classified taking into account different characteristics such as continuos vs. discrete, analog vs. digital, periodic vs. aperiodic, finite vs. infinite, deterministic vs. random.

For instance in the case of the EEG signal (although this can be extrapolated to the other electrophysiological signals used in this thesis), we are dealing with a continuos analog signal.

But once we record it and store it in a electronic support, the signal becomes discrete and digital. This is due to the fact that when we use an amplifier to record an EEG signal, we have to set a recording sampling rate and thus we convert the "real world" EEG signal (continuos) to a discrete signal. A similar argument holds for the conversion of the signal from analog to digital. The "real world" EEG is analog, that is, its voltage can take any continuous value from its minimum voltage to its maximum voltage. Once we record it with an amplifier, another quantisation is applied but this time in the voltage dimension, i.e. in the y-axis. Regarding the rest of the characteristics of the EEG signal, it is finite, aperiodic and not deterministic. In reality, the biological processes that generate the EEG signal are deterministic, but as it is impossible to describe them in a microscopic way, and besides the amplifier always generates some amount of noise during the recording process, the EEG signal could be considered random. In any case, there are methods to determine if a signal is deterministic or random, such as the one used in (Li et al. [5]), where they concluded that EEGs from schizophrenic patients were not deterministic.

Several methods are used in SP to extract features from electrophysiological signals, such as spectral analysis (Fourier Transform, wavelet, time-frequency,...), time domain features such as statistical information (mean, standard deviation, skewness, kurtosis, ...) and also other type of features such as Energy, Entropy, Fractal Dimension, autocorrelation for single channels... . Other types of interesting features look for the relationship between 2 or more channels. In this group of features we can find correlation analysis, Mutual Information (MI) which is based on Entropy, Coherence (CO) and Synchronisation Likelihood (SL). Many of these methods have been applied in the analysis of the data of this thesis, and they will be explained in their corresponding sections.

A very complete review of signal processing techniques applied to EEG data analysis, and in particular to BCI interfaces, can be found in (Bashashati et al. [3]).

1.4 Electrophysiology

Electrophysiology is the branch of physiology that deals with the electrical properties of living organisms, from a microscopic scale (i.e. action potential of a single neurone) to a macroscopic perspective (electrical activity generated by a whole organ such as the heart or the brain).

Many techniques of electrophysiology deal with microscopic recordings, which are out of the scope of this work, but are worth mentioning. We can divide these recordings in two classes: intracellular and extracellular. In the intracellular techniques, the most popular technique is called the Patch-Clamp technique developed in 1978 by Erwin Neher and Bert Sakmann (Neher et al. [6]) who received the Nobel Prize in Physiology in 1991. A microelectrode is placed close to a cell and a gentle suction is applied to draw a piece of the cell membrane (the 'patch') into the microelectrode tip. This configuration is called the "cell-attached" mode, and it can be used for studying the activity of the ion channels that are present in the patch of membrane. Other configurations can also be done, such as the 'whole cell' mode or the 'perforated patch' mode.

The techniques used for extracellular recording are the single-unit recording, the Local Field Potentials (LFP) recording and the amperometry. The single-unit recording is accomplished

by introducing a microelectrode with a tip of about 1 micrometer in the brain of a living animal. This electrode will usually detect the activity of at most one neurone. The LFP is a particular electrophysiological signal which is related to the sum of all dendritic synaptic activity within a volume of tissue and it can be recorded using a low impedance extracellular microelectrode, placed sufficiently far from individual local neurones to prevent any particular cell from dominating the electrophysiological signal. Finally the amperometry technique uses a carbon electrode to record changes in the chemical composition of the oxidised components of a biological solution. Oxidation and reduction is accomplished by changing the voltage at the active surface of the recording electrode in a process known as "scanning". Because certain brain chemicals loose or gain electrons at characteristic voltages, individual species can be identified.

In the case of the studies presented in this thesis, we did not work with such microscopic techniques. Instead we used macroscopic signals. In the next list we can see the specific names of particular electrophysiological readings:

- Electrocardiography (ECG) - for the heart
- Electroencephalography (EEG) - for the brain
- Electrocorticography (ECoG) - for the cerebral cortex
- Electromyography (EMG) - for the muscles
- Electrooculography (EOG) - for the eyes
- Electroretinography (ERG) - for the retina
- Electroantennography (EAG) - for the olfactory receptors in arthropods

During my research, we worked mainly with EEG, ECG, EOG and EMG. A very good review of the origin of these signals and their recording methods can be found in Andreassi [7]. In the next subsections a special attention to these signals will be taken.

1.4.1 Electroencephalography

The normal functioning human brain generates both electric and magnetic fields. These fields are the result of the summation of the electrical signal from flows of ions, as neurones, primarily in the cerebral cortex, respond to various stimuli. The cerebral cortex is made up of between 10^9 and 10^{10} neurones and the summated electrical signal from these cells is in fact a unique measure of human brain function. The summated electrical field is easily measured using electrodes attached to the scalp and an appropriate amplification system (Remond [8]). This measured electrical signal is known as the electroencephalogram (EEG). The EEG is a signal that is representative of the summated electrical activity of the functioning human brain. The main source of the EEG is, then, the synchronous activity of thousands of cortical neurones. Measuring the EEG is a simple non-invasive way to monitor electrical brain activity, but it does not provide detailed information on the activity of single neurones (or small brain areas).

Moreover, it is characterised by small signal amplitudes (of the order of the μVolts) and noisy measurements (especially if recording outside shielded rooms).

The EEG is present from before birth (actually non-natal brain electrical activity can be recorded using a foetal MEG) until death. In fact, in some places death itself is defined by the absence of an EEG, the so-called 'brain death'. The EEG represents a set of field potentials as recorded by multiple electrodes on the surface of the scalp. The set of locations for electrodes placed on the skull is called a montage.

Historically four major types of continuous rhythmic sinusoidal EEG waves are recognised (alpha, beta, delta and theta). There is no precise agreement on the frequency ranges for each type. In the list below we have also described other standard brain rhythms as well.

- Delta waves are in the frequency range up to 4 Hz and are often associated with the very young and certain encephalopathies and underlying lesions. Delta waves are also seen in stage 3 and 4 sleep.
- Theta waves frequency range goes from 4 Hz to 8 Hz and is associated with drowsiness, childhood, adolescence and young adulthood. This EEG frequency can sometimes be produced by hyperventilation. Theta waves can be seen during hypnagogic states such as trances, hypnosis, deep day dreams, lucid dreaming and light sleep and the preconscious state just upon waking, and just before falling asleep.
- Alpha (or Berger's) waves fall in the frequency range from 8 Hz to 12 Hz. They are characteristic of a relaxed, alert state of consciousness and are present by the age of two years. Alpha rhythms are best detected with the eyes closed. Alpha waves attenuate with mental exertion and the opening of the eyes, and are best seen over the posterior regions. An alpha-like normal variant called mu is sometimes seen over the motor cortex (central scalp) and attenuates with movement, or rather with the intention to move.
- Sensorimotor rhythm (SMR), also known as mu-rhythm, is a middle frequency (about 12-16 Hz) associated with physical stillness and body presence.
- Beta waves have a frequency from 12 Hz up to 30 Hz. Low amplitude beta waves with multiple and varying frequencies are often associated with active, busy or anxious thinking and active concentration. Rhythmic beta with a dominant set of frequencies is also associated with various pathologies and drug effects.
- Gamma waves are in the frequency range of approximately 30 Hz to 90 Hz. Gamma rhythms appear to be involved in higher mental activity, including perception, problem solving, fear, and consciousness.

Rhythmic slow activity in wakefulness is common in young children, but is abnormal in adults. In addition to the above types of rhythmic activity, individual transient waveforms such as sharp waves, spikes, spike-and-wave complexes occur in epilepsy, and other types of transients occur during sleep. In the transition from wakefulness, through Stage I sleep (drowsiness), Stage II (light) sleep, to Stage III and IV (deep) sleep, first the alpha becomes intermittent and attenuated, then disappears. Stage II sleep is marked by brief bursts of highly

rhythmic beta activity (sleep spindles) and K complexes (transient slow waves associated with spindles, often triggered by an auditory stimulus). Stage III and IV are characterised by slow wave activity. After a period of deep sleep, the sleeper cycles back to stage II sleep and/or rapid eye movement (REM) sleep, associated with dreaming. These cycles occur about 4 times during the night, considering a healthy 8 hour sleep.

Research aiming to extract genetic information from the human EEG began as early as 1938 (Berger [9]), but first results became available only after 1955, (Juel-Nielsen and Harvald [10]). More specifically, the research carried out was focused on three different cases. In the first case, EEGs from members of the same family were investigated and compared (Vogel [11], Anokhin et al. [12], Eischen et al. [13]). In the second case, the common characteristics between the EEGs of monozygotic and of dizygotic twins were sought (Stassen et al. [14], Sviderskaya and Korolkova [15]). In the third case, different EEGs were compared, which came from the same person; the objective was to extract more or less invariant characteristics that would characterise the individual (Poulos et al. [16]).

Pioneering research into brain activity in the alpha and beta rhythms of the EEG was conducted by (Juel-Nielsen and Harvald [10]) and (Vogel [11]), and subsequently by other researchers (Plomin [17]). In these works it has been shown that alpha and beta rhythms contain significant brain activity frequencies, in the sense that individual genetic characteristics are contained therein.

The methods used to reach that conclusion were initially supported by teaching aids which, were observed by sight. Therefore, the results were unreliable. Thanks to the progress in computerised data processing, it became possible for the EEG signal to be analysed digitally with parametric and nonparametric methods (Varner et al., 1991, Poulos et al. [16], Hazarika and Sergejew [18]). Further progress was made possible thanks to the development of artificial neural networks (Hazarika and Sergejew [18]) and other methods of pattern recognition. Most of the previous research effort, however, has been focused on the classification of pathologically induced EEG variants due, for example, to epilepsy or schizophrenia, for diagnostic purposes. Along this line, recent research including linear and non-linear approaches with a neural network classification scheme has reached a 71% classification score (Hazarika and Sergejew [18]). A key observation in these approaches is the fact that a given pathology induces a pathology - specific variation pattern on the "healthy" EEG signal. Diagnosis of the pathology is therefore based on the detection of the specific variation pattern, which thus serves as a classification feature.

The EEG is usually monitored using a device called an electroencephalograph and is displayed as continuous changes of voltage over time. The EEG recording is obtained by attaching a number of electrodes on the scalp (either using some type of special conductive glue or more commonly these days by wearing an elastic cap), usually after preparing the scalp area by light abrasion and application of a conductive gel to reduce impedance. The recording electrodes are typically placed in standardised locations over the main anatomical structures of the brain such as the frontal, temporal or parietal lobes. Figure 1.2 shows some of the standardised locations where electrodes could be placed.

Each electrode is connected to an input of a differential amplifier (one amplifier per pair of electrodes), which amplifies the voltage between them (typically 1,000-100,000 times, or 60-100 dB of voltage gain), and then displays it on a screen or inputs it to a computer. The amplitude of the EEG is about 100 μV when measured on the scalp, and about 1-2 mV when measured on the surface of the brain. This invasive technique is called electrocorticogram (ECoG) and requires surgery.

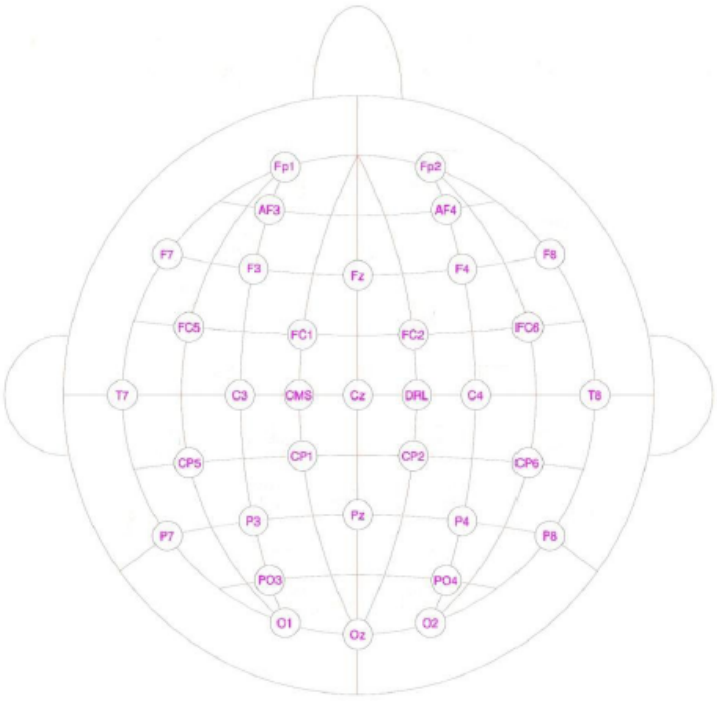

Figure 1.2: Standard 32 EEG electrodes 10-20 placement

1.4.2 Electrocardiography

Electrocardiography (ECG) is a method to measure and record different electrical potentials of the heart, developed by Willem Einthoven in the early 1900s (Einthoven [19], Einthoven [20]). He was awarded the Nobel Prize in Medicine in 1924. The origin of the electrical activity measured by ECG is in the muscle fibres of different parts of the heart. The ECG registers this activity and provides an output consisting in the trace of the heartbeats, including heart rate (or heartbeat period) and shape of the heartbeats.

A heartbeat is the physical contraction of the heart muscle caused by chemical/potential differences in the component cells called myocytes. The myocytes have negatively charged interiors. The heartbeat begins with the firing of the Sino-atrial (SA) node, the heart's dominant pacemaker. The electrical signal radiates outward causing the myocytes to depolarise and compress rapidly by a movement of sodium (NA+) ions from the extracellular medium to the intracellular one. This is expressed as the P wave in the ECG trace. The depolarisation rate slows dramatically when the signal hits the atrio-ventricular (AV) node, where the chemical signal changes to relatively slow moving potassium (K+) ions from the intracellular medium to the extracellular one. The change in contraction is expressed as the gap between the P and the R complexes. Once past the AV node, the signal passes through to the cells lining the ventricles. The ventricles contract rapidly, which produces the R complex. Repolarisation does not exactly mirror polarisation due to the chemical agents and the lag between the end of the electrical impulse and physical displacement (Dubin [21]). The heart rate is controlled by the autonomic nervous system (ANS). The ANS is composed of the sympathetic and parasympathetic system. Each of the two systems has independent ganglia and secretes neurotransmitters. The sympathetic system stimulates the cardiovascular system by increasing the rate of SA node firing, increasing the myocyte cell conductivity, and increasing the

force of contraction. The results of the sympathetic secretion of neurotransmitters are: a) the reduction of the inter beat interval due to the increased SA firing rate, and b) the reduction in the width of the P and T complexes due to increase conductivity. The parasympathetic system has the opposite effect.

The ECG signal measures the change in electrical potential over time. The trace of each heartbeat consists of three complexes: P, R, and T. These complexes are defined by their corresponding fiducial points, which correspond to the peak of each complex. The labels in Figure 1.3 document the commonly used medical science ECG fiducials. The ECG may roughly be divided into the phases of depolarisation and repolarisation of the muscle fibres making up the heart. The depolarisation phases correspond to the P-wave (atrial depolarisation) and QRS-wave (ventricles depolarisation). The repolarisation phases correspond to the T-wave and U-wave (ventricular repolarisation). The elements in the ECG-complex are shown in Figure 1.3.

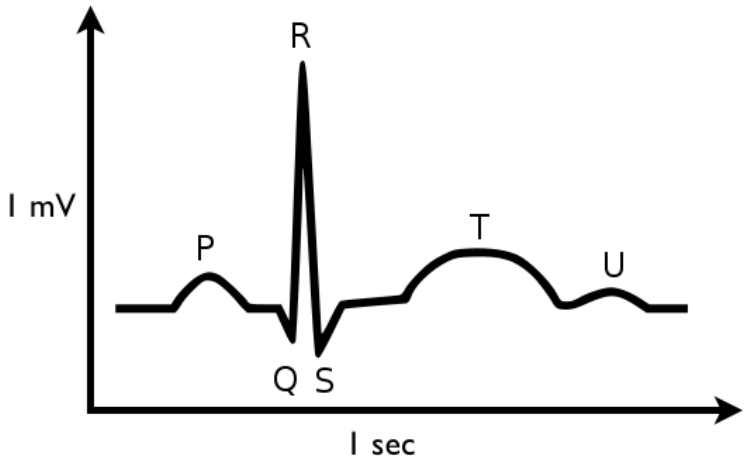

Figure 1.3: Elements of the ECG-complex

Electrocardiogram (ECG) data are traditionally acquired for clinical diagnosis of cardiac function. (Dubin [21]) describes the link between cardiac function and the expression of the ECG trace. In addition, he offers a set of rules for ECG interpretation. However, Dubin's work uses analogue methods for applying these rules. With the advances in computational power and medical instrumentation, hardware/software systems have been developed for assisted ECG trace interpretation.

The ECG trace contains a wealth of information. Researchers have been using ECG data as a diagnostic tool since the early 20th century. Only in the last 20 years, however, have researchers been able to apply digital analysis to the data. The most common digital application is the Heart Rate Variability (HRV) (Malik [22]). Researchers have applied numerical methods to more complex diagnostic interpretation tasks such as separating mother-foetal signal, identifying atrial and ventricular fibrillation, myocardial infarction and recently to characterise the uniqueness of the ECG to an individual (Biel et al. [23], Hoekema et al. [24], Jang et al., 2001, Irvine et al., 2001). Except for the HRV studies, each researcher has developed ad hoc features.

Over the years, the interindividual variability of the ECG and the VCG (vectorcardiogram), has been studied by several groups (Jang et al., 2001, Irvine et al., 2001, Marieb, 2003). The

VCG is a technique that allows us to extract a graphical representation of the magnitude and direction of the electrical currents generated by the heart in a cardiac cycle, in the form of a vector loop. It is usually produced by an oscilloscope which simultaneously records 3 standard ECG leads. These studies were based on observations made on large numbers of subjects. Impressive lists of (ranges of) normal values on just about any parameter used in the world of ECG and VCG can be found in the part III of the momentous series "Comprehensive Electrocardiology", edited by P.W. Macfarlane and T.D. Veitch Lawrie (Macfarlane [25]).

In a paper by (van Oosterom et al. [26]), an overall view on some of the basic aspects of ECG variability in normal subjects was presented. The paper was based on test results from 25 subjects for which electrical data (ECG and VCG) as well as a unique set of matching geometrical data, from Body Surface Mapping (BSM) and Magnetic Resonance Imaging (MRI), was available. The final objective of the paper was to contribute to the search for methods to reduce the interindividual variability of ECG, which poses a limitation on the diagnostic accuracy of the ECG. The underlying hypothesis is that, next to interindividual differences in the electrophysiology of the heart, timing of the depolarisation and repolarisation, a major source of variability can be attributed to differences in the geometrical relationships involved in heart position and orientation, torso shape as well as to lead placement relative to heart position. Moreover, it is assumed that the electrophysiological factors and the geometrical factors can be treated as contributing independently to the variability of the ECG.

Various measures for quantifying the interindividual variability of the ECG and the VCG in healthy subjects were thus carried out, as well as an analysis of factors that may cause this variability, in particular of the geometrical factors of body size, heart size, heart position and orientation. The results indicate that the variations in the magnitude of the ECG as observed through leads placed on the anterior thorax are dominated by the solid angle at which the outline of ventricular mass is seen from points on the thorax. Heart size and body size as such play only a secondary role. The limited spatial sampling of the anterior thorax directly overlaying the heart causes the mean values of all measures of amplitudes in females to be lower than in males. The VCG magnitude was found to be much less dependent on overall geometry and heart position, and, hence, also to be less dependent on gender.

In recent papers, a more extensive set of ECG descriptors that more completely characterise the trace of a heartbeat has been proposed. Those ECG descriptors contain information about the physiology of an individual's heart, rather than some visual expression of traits, making them suitable for person recognition purposes.

The standard clinical ECG is measured by placing ten electrodes on selected spots on the human body surface. Six electrodes are placed on the chest, and four electrodes are placed on the extremities. The ECG is measured with respect to an arbitrary baseline. The magnitude of the electrical potential varies with the placement of electrodes relative to the heart. Diagnosticians have exploited the change in information with sensor placement to improve their understanding of cardiac performance.

For regular ECG recordings, the variations in electrical potentials in 12 different directions out of the ten electrodes are measured. These 12 different electrical views of the activity in the heart are normally referred to as leads. The 12 leads are made up of three bipolar and nine monopolar leads. The three bipolar leads are the electrical potentials between the right and left arm (lead I), the right arm and left foot (lead II), and between the left arm and left foot

(lead III). For the monopolar leads, four different artificial reference points are constructed. These reference points are the average of the signals seen at two or more electrodes. Using these reference points, the potentials appearing on the left arm (aVL), the right arm (aVR), the left foot (aVF), and on the six chest electrodes (V1-V6) are measured. The right foot is normally used for grounding purposes only.

In the past, there have been many approaches to automatically generate diagnostic ECG classification based on the 12-lead electrocardiogram. Both statistical methods and artificial neural networks have been used (Degani [27], Bozzola et al. [28], Silipo and Bortolan [29]).

1.4.3 Electrooculography

The Electrooculography (EOG) is a technique used to record eye movements and blinks. The recordings, called electroocculograms, are usually made by attaching a pair of electrodes in a bipolar montage horizontally at the corner of the eyes. This setup allows the recording of horizontal eye movements. Another pair of electrodes are also often placed above and below one of the eyes to record vertical movements. The eye blinks are also easily detected with this vertical setup.

The basis of the EOG is that the eyes act as an electrical dipole. There is a steady electrical potential difference (approximately 0.40-1 mV) between the cornea and the retina of the eyes, the cornea being the positive pole.

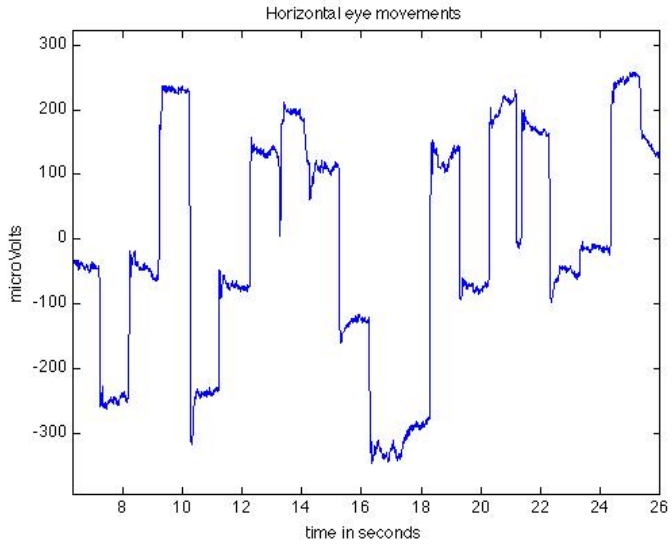

Figure 1.4: Sample of an EOG recording with the ENOBIO sensor. The electrodes were placed horizontally in the corner of the eyes and thus the horizontal movement of the eyes can be observed

A well-known fact in EEG recordings is that this signal is often contaminated by EOG artefacts (and also by EMG artefact). This is due to the fact that the EOG signals are of high amplitude (up to 0.5 mV), and EEG electrodes placed close to the eyes can detect these signals easily. In fact, even the electrodes placed in the occipital area can detect EOG

signals, but in a much more smooth way. In order to clean EOG artefacts from the EEG recordings, several methods have been implemented, based on different techniques such as Independent Component Analysis (ICA), Wavelets and so on. In section 4.3.1, we present an original method to correct EOG artefacts. A review of the different EOG artefact correction techniques can be found in (Croft and Barry [30]).

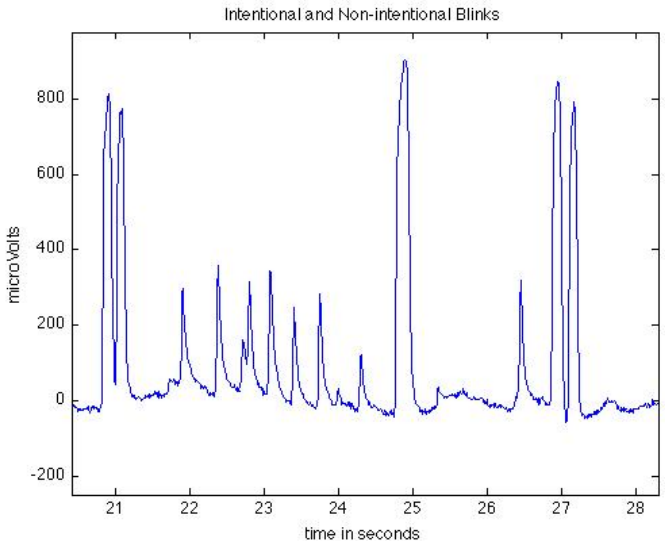

Figure 1.5: Sample of an EOG recording with the ENOBIO sensor. The electrodes were placed above and under the right eye and thus the eye blinks can be observed

1.4.4 Electromyography

Electromyography (EMG) is the technique related with the measurement of the electrical activity generated by the contractions of the muscles fibres. Although EMG can be recorded with thin needle electrodes, in most cases the recording is performed with surface electrodes. Those electrodes are usually placed in a bipolar configuration, separated a few centimetres over the muscle under study. These electrodes record the sum of a large number of depolarisations that occur when a group of motor units are activated, prior to the contraction of the muscle.

The recorded signal using EMG techniques is called electromyogram (also abbreviated as EMG). The frequencies of interest of the EMG signal goes from 20 to 200 Hz, although frequencies as low as 1 Hz and up to 1000 Hz might be observed. The amplitude usually goes from 1μV to 50 μV. Again, depending on the size of the muscle and on the degree of contraction of the fibres, amplitudes as high as 1000μV can be observed.

The EMG is not a regular signal compared to other electrophysiological recordings, such as the alpha wave of the EEG or the blinking patterns of the EOG. That is why a feature often used in EMG recordings is the integrated surface EMG: the total amount of electrical activity over a period of time is computed.

As in the case of EOG, EMG also affects EEG recordings. This is due to the fact that humans have a large number of muscles in the head and around the scalp. The movement of

these muscles generates strong signals easily detected in EEG recordings. As in the case of EOG, several techniques are used to correct the EEG signals from those muscular artefacts, the most common one being the use of filters.

In this work we present a pioneering study we conducted where the use of the EMG recorded from both forearm flexors was used as a biometric feature for identification/authentication purposes. A deeper explanation of this work can be found in Annex D where a chapter called 'Electrophysiological Biometrics: Opportunities and Risks', published in a book named 'Second Generation Biometrics' by Springer, is presented (Riera et al. [31]).

Chapter 2

Objectives

The main objective of this thesis is explained in its title: 'Computational Intelligences Techniques for Electro-Physiological Analysis'. The main idea is to use tools from the Computational Intelligence field to analyse different EEG data sets, although some work on other electrophysiological signals has also been done. An important part of this work also includes the extraction of relevant features from the EEG signals, which is related with the field of Signal Processing. These different concepts have been deeply explained in the previous sections 1.2 and 1.3. In this part we want to state in a few lines the main objectives of this work.

- Objective 1: Extract valuable information from EEG signals to build new applications. This generic objective summarises the main topic of this work. It is well known that valuable information can be extracted from EEG signals. For instance EEG is used as a diagnostic tool for several brain pathologies such as epilepsy and sleep disorders. EEG signals have also been widely used to build Brain Computer Interfaces (BCI) applications. In the case of this work, we have studied EEG signals for other applications that we consider quite novel.

- Objective 2: Study the potential of the EEG signals for biometric purposes. This objective includes a large data collection campaign and a study of different EEG features to find the ones most suited for a biometric system. As a note, we have also largely worked with ECG signals and to a lesser degree with EOG and EMG signals.

- Objective 3: Develop as unobtrusive a system as possible for EEG and ECG biometric, ideally using both modalities at the same time to increase the robustness.

- Objective 4: Study the potential use of EEG to discriminate between different populations of First Psychotic Episode (FPE) patients. These populations include FPE patients later diagnosed as schizophrenics, FPE patients that were not diagnosed as schizophrenics, schizophrenics after taking medication and finally a control group.

- Objective 5: Apply advanced signal processing techniques, such as complex networks and computational intelligence techniques to maximise the discrimination between the different FPE groups.

- Objective 6: Develop a protocol to induce different levels of stress and carry on the data recording campaign.
- Objective 7: Find stress markers in the EEG signals.

In the next 3 chapters we will present 3 different researches in which CI techniques, including ML, have been applied to electrophysiological data analysis, mainly to EEG. In the first one, we have tested the potential of EEG and ECG for biometric purposes. In other words, the questions we asked to ourselves was: are EEG and ECG potentially useful for authenticating/identifying people?

In the next research presented in this thesis, we have looked for EEG differences between a healthy control group and a group of First Psychotic Episode (FPE) patients. If we were able to find meaningful differences in EEG features from both groups, we would have a powerful tool for schizophrenia diagnosis, and actually, that was the motivation for our work.

Finally, in the last research described in this thesis, we have studied emotional markers in the EEG signals. In order to do so, we implemented a protocol and carried out an experiment in which participants were asked to perform different tasks. These tasks were specially selected to induce different feelings in the participants.

Chapter 3

Biometry based on Electrophysiological Signals

Biometry is a growing field of research in which millions of dollars are invested each year. Since the 9/11 terrorist attack, security has increased and biometric applications have gained more attention than ever. There are many types of biometric systems depending on which biometric trait is being used for authentication. Some of the most common ones are fingerprint, face recognition, voice recognition and Iris scan. These are in some degree unobtrusive, but it is also important to take into account that these systems are not perfect since it is possible to spoof them in a relatively simple manner. For instance, the work of Matsumoto et al. [32] shows that using material worth a few dollars, most commercial fingerprint biometric systems are easily spoofed.

The European co-funded project TABULA RASA (Trusted Biometrics under Spoofing Attacks under the Research area: ICT-2009.1.4 Trustworthy ICT), in which we have been involved, deals with the study and implementation of countermeasures to possible spoofing attacks to biometric systems. On the other hand there are more reliable biometric systems such as DNA tests, but in this case, the level of invasiveness is rather high and not suitable for use on a daily basis.

There are also more recent types of biometric systems based on different traits, in which a big interest has been shown in the last decade. For instance we have gait, ear shape, keystroke, retina and finally electrophysiological traits such as ECG and EEG. In this chapter, our research on electrophysiological biometrics will be described. During this research, some works have been published and they have been inserted in this document for convenience. Below follows a list of these publications.

- a Journal Paper (Riera et al. [33]) describing our work in EEG based biometrics (included in section B).
- a Book Chapter entitled "Multimodal Physiological Biometrics Authentication" in a book called "Biometrics: Theory, Methods, and Applications" published by John Wiley and Sons, Inc. in 2009 (Riera et al. [34]), in which our work on EEG biometrics, ECG biometrics and the fusion of both modalities is described (included in Annex C).

- a Book Chapter entitled "Electrophysiological Biometrics: Opportunities and Risks" in a book called "Second Generation Biometrics" published by Springer in 2010 (Riera et al. [31]), in which our work on Electrophysiological signals for biometric purposes (including EEG, ECG, EMG, EOG and a BCI biometric system) is described (included in Annex D).
- a Conference Paper (Riera and Dunne [35]) describing an application of an EEG based biometrics system in Virtual Environments (included in Annex E).
- a Conference Paper (Soria-Frisch et al. [36]) focusing on the fusion of different biometric signals, including EEG and ECG among other biometric traits (included in Annex F).

The different electrophysiological signals we have used for biometric purposes are EEG and ECG. We have also fused the classification results of both systems in order to obtain a more reliable classification results. We have also worked with EMG and EOG signals for biometric purposes but just as a proof of concept. Finally we also describe a biometric system based on BCI. Our work on EMG, EOG and BCI is pioneering since, to our knowledge, no work has been published before in this field.

3.1 State of the Art Biometry based on Electrophysiological Signals

In this section we will review some works from the scientific literature where EEG and ECG have been used for biometric purposes.

3.1.1 EEG as a biometric trait

Several works have been published describing the potential use of EEG as a biometric trait. In this section we will describe some of these works and highlight their main innovations.

A scientific team from the Ionian University in Greece has published several works in this topic (Poulos et al. [16], Poulos et al. [37], Poulos et al. [38], Poulos et al. [39]). In their study five data types were selected. For each one of 4 subjects, named A, B, C and D, a set of forty five (45) EEG recordings were taken. In addition, one EEG recording was taken from each one of 75 different subjects to form a group named X. The final pool of EEG recordings thus contained (4 x 45 + 75 x 1 = 255) recordings. Both male (76%) and female (24%) subjects formed group X, subjects A, B and C were male and subject D was female. Ages ranged from 19 to 60 years and it was determined that none of these subjects had chronic or acute health problems or used any prescribed medication. Furthermore EEG recordings including nontypical parts, such as artefacts, are excluded from the set after inspection by a physician.

Subjects were at rest, with closed eyes. Voltage difference (in μV) was recorded between leads O2 and CZ (one channel). All EEG recordings lasted for 3 continuous minutes, thus producing a 23040 samples long record each, at a 128 Hz sampling rate. Recordings were

filtered using a 1-30Hz low pass filter to retain spectral information present in the four major EEG rhythms (alpha, beta, delta and theta).

The use of different methods for EEG signal processing was investigated; the methods tested varied in (i) features extracted from the EEG signal and (ii) the classification method employed, as follows:

1. Fast Fourier Transform (FFT) features - Computational Geometry (CG) classification (Poulos et al. [16]). They reach a Classification Rate (CR) equal to 91%.
2. FFT features - Learning Vector Quantisation (LVQ) classification (Poulos et al. [38]). In this work they perform two test cases. Test case 1 aims to differentiate between individual A and 'non-A' individuals, the group X members serving as the 'non-A' class in that case. They did the same with individuals B, C and D. Test case 2 addresses a multi-target setup, where four individuals of interest, namely A, B, C and D, are to be classified, in contrast to test case 1. Spectral values of the EEG signal were computed and the alpha rhythm frequency band (7-12 Hz) was retained for further processing. Alpha rhythm frequencies were next partitioned into three overlapping frequency bands of 3 Hz each (7-10 Hz, 8-11 Hz, 9-12 Hz). The respective CR for each frequency band were 87,9%, 90,6% and 90,4% for test case 1 and 91%, 94% and 95% for test case 2.
3. Autoregression (AR) modelling features - CG classification (Poulos et al. [37]). Using this technique they reach a CR equal to 95%.
4. AR modelling features - LVQ classification (Poulos et al. [37]). Using this technique they reach CRs between 72% and 84%.
5. AR non-linear (ARnl) model features - LVQ neural network classification (Poulos et al. [39]). In this work they also performed two test cases (the same as in Poulos et al. [38]). They reached a CR of 78,4% for AR features and 80,7% for ARnl features in test case 1. In test case 2 they reached 68% and 78% respectively.

Another work worth to describe is (Paranjape et al. [40]). This paper examines the effectiveness of the EEG as a biometric for the identification of individual subjects in a pool of 40 healthy subjects. In this paper the authors focus on recordings from the P4 electrode. The signal from the P4 electrode is relatively strong and typically contains the alpha rhythm. They speculate that using multi-channel data from all EEG electrodes can enhance the results obtained from this single-channel recording.

A data set of 8-channel EEG recordings from 40 healthy volunteers was used in this study. The subject's EEG was recorded while performing the simple activity of resting with eyes open (EO) and resting with eyes closed (EC). Electrodes were placed over the frontal (F7, F8), temporal (T3, T4, T5, T6) and parietal (P3, P4) lobes of the brain in accordance with Figure 1.2. Recordings were carried out over an extended period of time with data stored in epochs of 8.533 sec duration. A trained neurologist evaluated the epochs and those epochs containing appreciable muscle (EMG), cardiac (ECG), or other noise signals were removed from the data set. Thus, while each epoch contained contiguous data, epochs were not necessarily contiguous in time. For each subject typically there were about 8 epochs available. Each

epoch was composed of 1024 digital samples of EEG data acquired at a sampling rate of 120 samples/second for each one of the 8 electrodes.

In this work, the authors examine the characteristics of the EEG as a biometric by examining Autoregressive (AR) models that are representative of the second order statistics of the EEG. Autoregressive models of various orders are computed for a selected number of EEG epochs. In this work, the concept of the AR model coefficients of the EEG having some biometric potential is first graphically demonstrated with low order autoregressive models. By showing that there is a natural clustering of AR coefficients, the idea that individuals may be uniquely identified is suggested.

They developed Autoregressive models for single EEG traces using the Lattice Equivalent Model and Levinson Recursion. Model orders from 3 through 21 were generated rapidly and efficiently using this method. As the order of the model increases, the accuracy of the model as a predictor of the next value in the EEG time series is increased.

In order to evaluate further the biometric characteristics of the AR model parameters, discriminant function analysis was applied to the full EO EEG data set. This was followed by the computation of a discriminant function to try to distinguish individual subjects in the data set. Discriminant analysis was performed as a two-stage process. First the total variance/covariance matrix for all variables is computed, and then the within-groups variance/covariance matrix is computed. The two matrices are then inverted and a function is computed that minimises the variance within group while maximising the variance between groups.

In a second step, and in order to determine if the discriminant analysis in fact shows a true clustering of AR coefficients that is unique to the individual, the data was divided into two equal sets and the discriminant functions were computed using the training data set and tested using the test data set. Both the training set and the test data set have data from 40 subjects. There are only fewer epochs for each subject in each data set. They reach almost a perfect classification for the training set using AR models of order above 11. Regarding the test set, the maximum perfomance they reach is 85% for an AR model of order 15.

In the work (Ravi and Palaniappan [41]) we find an interesting method to select the best electrode location for authentication based on genetic algorithms (GA). The fusion of GA with linear discriminant classifier shows that the identification performance of EEG signals from 40 subjects does not degrade when using 23 selected channels as compared to all the available 61 channels as studied previously. As the channel identification method by GA is general, it could be used in any feature reduction application.

Finally we also want to include the work of Nicolaou and Nasuto [42] even though it does not deal with biometry. They propose a sophisticated method for automatic artefact removal from EEG. Since in the project ACTIBIO (see annex A) we will record EEG in a non-constraint manner (the subject will be free to perform any action) the artefact detection and removal will be an important part of the research, performed in an automatic manner. Their paper investigates the robustness of Mutual Information based features to inter-subject variability for use in an automatic artefact removal system. The system is based on the separation of EEG recordings into independent components using a temporal ICA method, RADICAL, and

the utilisation of a Support Vector Machine for classification of the components into EEG and artefact signals. High accuracy and robustness to inter-subject variability is achieved.

In our case, we developed our own artefact corrector algorithm described in section 3.2.2. This work was done within the ACTIBIO project, where the subject is free to move while having her/his EEG (and ECG) recorded. Due to these movements, large movement artefacts are observed in both the EEG and EEG signals, and they need to be corrected. In fact we will see in the result section that the performance increases by applying this algorithm.

Figure 3.1: First generation ENOBIO Electrophysiological sensor

As a last comment before describing the methodology of this research, it is important to take into account that we have put as a priority the usability and unobtrusiveness of the system we have developed. That is why we have used the ENOBIO sensor as the recording device. It has 4 channels (plus the reference), it is wireless and wearable. Moreover, the sensor is very easy and quick to apply with the help of a head band, as shown in figure 3.1. We have focused on frontal electrodes, so the use of conductive gel is not needed anymore, or at least, if gel is used, it is easy to clean, compared to gel applied on hair. The sampling rate of ENOBIO is 250 Hz. There is another solution of ENOBIO, which allows placing the electrodes in any place of the scalp, as shown in figures 5.5 and 5.6.

3.2 EEG based Biometry Methodology

The different steps of the EEG data processing will be explained in this section. First of all, as the subject is free to move, an artefact correction module has been implemented in order to correct the parts of the signal polluted with movement artefacts. Once the signal has been corrected, a pre-processing module will filter and cut the signal in consecutive 4-second epochs. The next step is the feature extraction module. Several features are extracted for each one of these 4-second epochs. Finally, in order to perform the authentication, a classification is made and a binary decision is provided (either “authenticated” or “not authenticated”), along with a score and confidence level. In order to be able to perform the authentication, we have to enrol the subject. The way the subjects are enrolled will also be explained in the next paragraph.

3.2.1 EEG Enrolment

The enrolment recordings consist of four 2-minute takes. The subject is asked not to move while he is sitting on a chair watching a movie. That means that the subject keeps his eyes open and performs blinks during the enrolment.

Once we have the four enrolment takes of a given subject, we can extract his biometric signature. The overall architecture of the enrolment process is depicted in Figure 3.2. First of all, both EEG channels are referenced to the right earlobe electrode. That way we suppress all the common noise of the EEG channels and the right earlobe channel. Each EEG channel then undergoes the artefact correction process. The description of this module can be found in subsection 3.1. Then the next step is the data pre-processing. The signals are filtered between 1 and 40 Hz and then cut in 4-second epochs.

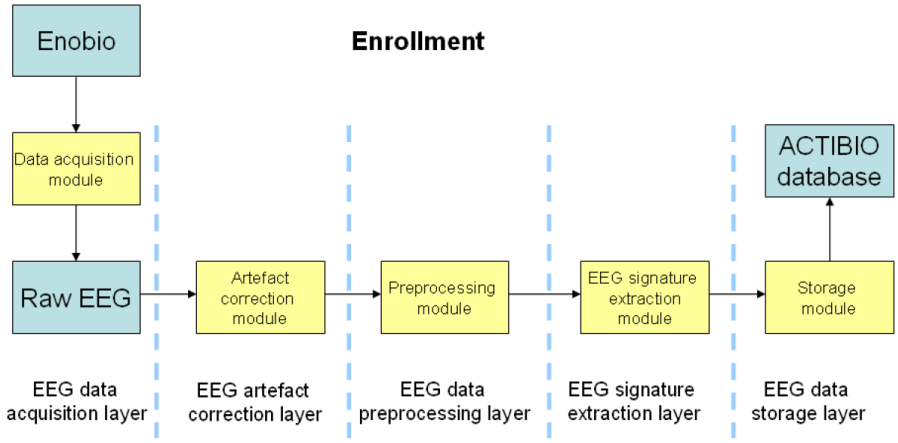

Figure 3.2: Scheme of the EEG enrolment process

The signals are now ready for the signature extraction module. Five different features are extracted to each 4-second epoch. Autoregression (AR) and Fourier transform (FT) are extracted for each one of the 2 channels. Mutual information (MI), Coherence (CO) and Cross-correlation (CC) are features that measure the different types of relationship between the 2 channels.

It is interesting to mention that other type of features, such as wavelets coefficients and synchronisation likelihood (defined in section 4.3), have also been tested. The conclusion after exploring different sets of features is that the more discriminative (and thus the more adequate for biometric purposes) are the ones described in the precedent paragraph.

We will perform a cross fold validation in order to personalise the features/channels and classifiers. The idea is to classify each enrolment take against the other three takes. The classifier we use is the Linear Discriminant Analysis (LDA) with 4 different Discriminant Functions (DF): linear, diagonal linear, quadratic and diagonal quadratic. For a given subject, the five best combinations of features/channels and classifiers will be the selected one for the future authentications. In total we have 28 possible combinations, as shown in Table 3.1.

The five best combinations of features/ channels and classifiers are stored in the ACTIBIO database for further recall during the authentication process. They are stored as trained classifiers in a binary format. This structure can be considered as the token for each subject.

Feature	Channel	Discriminant Function
AR	1	Linear
AR	1	Diag. Linear
AR	1	Quadratic
AR	1	Diag. Quadratic
AR	2	Linear
AR	2	Diag. Linear
AR	2	Quadratic
AR	2	Diag. Quadratic
FT	1	Linear
FT	1	Diag. Linear
FT	1	Quadratic
FT	1	Diag. Quadratic
FT	2	Linear
FT	2	Diag. Linear
FT	2	Quadratic
FT	1-2	Diag. Quadratic
MI	1-2	Linear
MI	1-2	Diag. Linear
MI	1-2	Quadratic
MI	1-2	Diag. Quadratic
CO	1-2	Linear
CO	1-2	Diag. Linear
CO	1-2	Quadratic
CO	1-2	Diag. Quadratic
CC	1-2	Linear
CC	1-2	Diag. Linear
CC	1-2	Quadratic
CC	1-2	Diag. Quadratic

Table 3.1: Combination of features, channels and classifiers

3.2.2 Motion Artefact correction

The electrophysiological signals are known to be noisy and easily contaminated by drifts, offsets and other artefacts due to subject movements, sweating or deficient contacts between the electrodes and the skin. ACTIBIO system will be unobtrusive, the data will be recorded while the subject is performing his daily duties and the signals obtained will not have the quality we can reach in a laboratory environment. It is necessary before analysing the data to clean the signal from undesired artefacts. A motion artefact correction module is applied to the data before applying the Authentication module. This section explains the steps followed in the development of this module. The difficulty is that the electrical signals generated by the motion of the subject are many times larger than the EEG signals. For this reason we would like to be able to identify the part of the recorded signal that is due to the motion of the subject and then subtract this component of the signal in order to make the EEG signals more usable.

As a first attempt we can try to identify common motion related artefacts. We could then model this signal burst and attempt to subtract this from the total signal. Suppose that we have identified a characteristic shape f(t) that seems to repeat in the signal and which we have reason to believe is due to motion. We want to develop a methodology to identify the location and characteristics of the occurrences of this shape. We will do so by computing a fit of this shape to each section of the data and by evaluating the fit parameters we can select those locations with a "good fit".

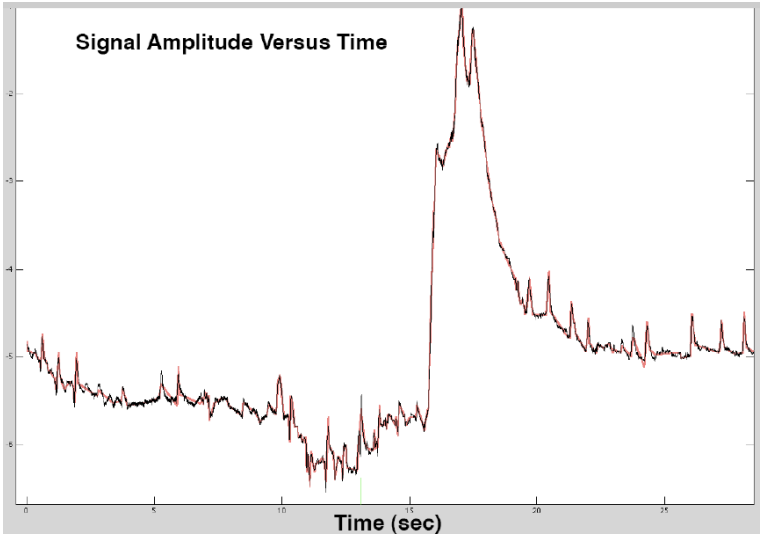

Figure 3.3: Red line is the artefact estimation computed by the algorithm that will be subtracted to the raw signal (black line)

In Figure 3.3 we can see the result of our artefact correction algorithm for a particular EEG recording. We see that the strong motion artefact that occurs between 15 - 20 seconds is very well detected. We can also see that most of the smaller peaks, which are generated by eye blinks, are also quite well detected. In Figure 3.4 we show the spectrum before and after applying the artefact corrector. We see that the spectrum power remarkably decreases in the low frequency range (between 0 and 20 Hz) after applying the artefact corrector. This is a typical result since motion artefacts (and EOG artefacts) are known to have low frequencies.

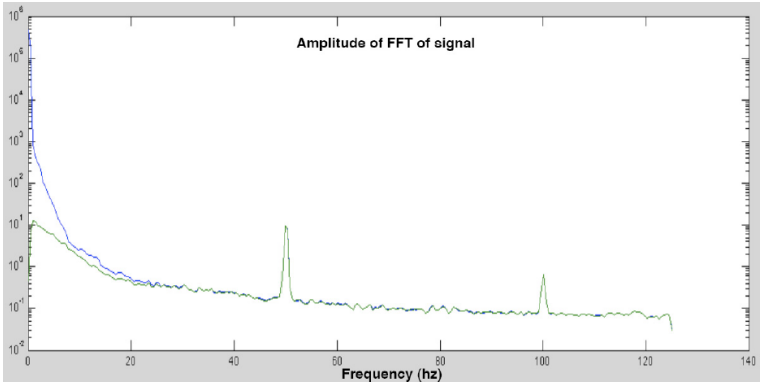

Figure 3.4: Spectrum before (blue) and after (green) applying the artefact corrector

3.2.3 EEG Authentication

The data processing performed in the authentication process is the same as the one done in the enrolment process, but in this case, the token is called from the ACTIBIO database and the classification is performed and the authentication results are output in the format: binary decision (either "authenticated" or "not authenticated"), along with a score (between 0 and 1) and confidence level (between 0 and 1). The overall architecture for authentication is depicted in Figure 3.5.

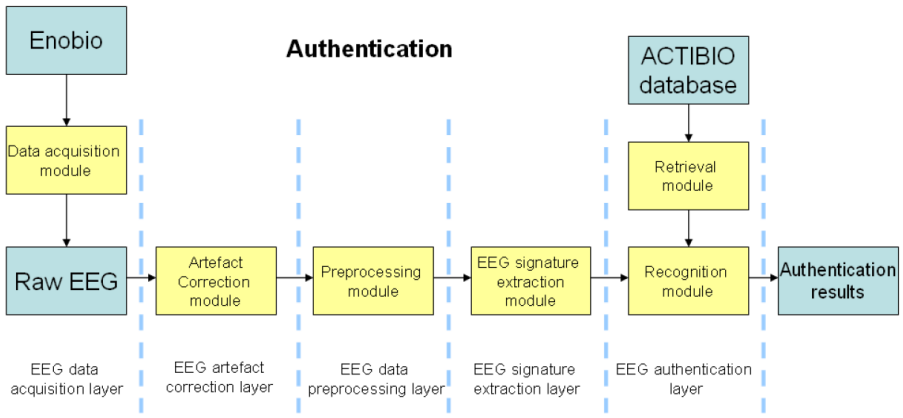

Figure 3.5: Scheme of the EEG authentication process

3.3 ECG based Biometry Methodology

The ECG based biometric module performs several steps. Each of them will be explained in this section.

First of all we record the whole sequence of ECG data. The raw data is shown in Figure 3.6.

In order to remove the drifts, it is a very common practice to apply a filter. In this case, we apply a band pass filter with frequency cut-offs of 0.5 Hz and 35 Hz. The filtered signal is presented in Figure 3.7.

At this stage, we remove the high peaks since they correspond to movement artefacts that distort the ECG signal. We apply a simple threshold: all the values higher than 1000 or lower than -1000 μV are discarded. We can see the result of removing those points in Figure 3.8.

In this case we see that very few points are removed, but if the movement artefacts were stronger, more points would have been removed. The algorithm also outputs the percentage of points removed. In this case the percentage is around 0.008 %. Indeed if the percentage of points is higher than 90%, the take would be discarded.

At this stage, we apply the peak detector to localise the R peaks in the ECG signal in order to cut each ECG waveform. In order to be sure that we are detecting all the R peaks in a correct way, we apply two conditions.

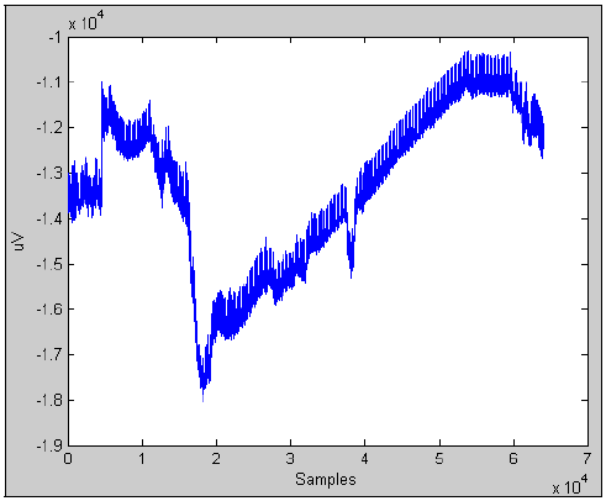

Figure 3.6: Sample of ECG raw data captured with ENOBIO. We can see typical low frequency drifts in the signal. We can also observe a high frequency drift around sample $0.5 * 10^4$. The ENOBIO sampling rate is 250 Hz

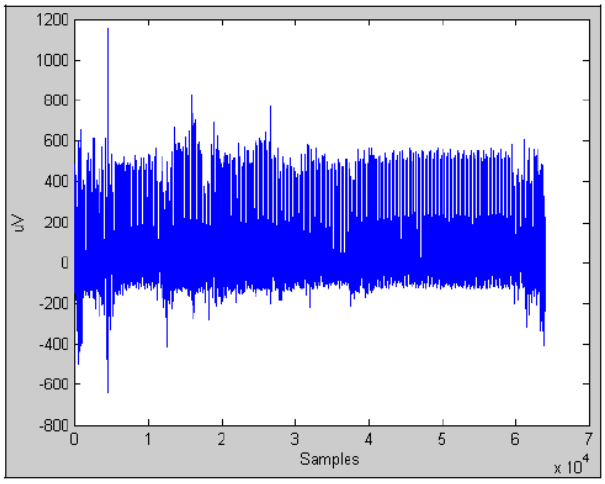

Figure 3.7: Band filtered ECG signal. We can see that the high frequency drift present in fig. 3.6 around sample $0.5 * 10^4$ appears now as a strong peak. The ENOBIO sampling rate is 250 Hz

- If the R-interpeak distance is smaller than 2/3 of the mean of the R-interpeak distances, we discard those ECG waveforms, since it probably means that we detected an incorrect peak between 2 R peaks.
- If the R-interpeak distance is bigger than 3/2 of the mean of the R-interpeak distances, we discard those ECG waveforms, since it probably means that we did not detect a correct R-peak.

This algorithm outputs the number of incorrectly detected peaks and the number of peaks not detected.

- Wrongly detected inter R-R peaks: 1

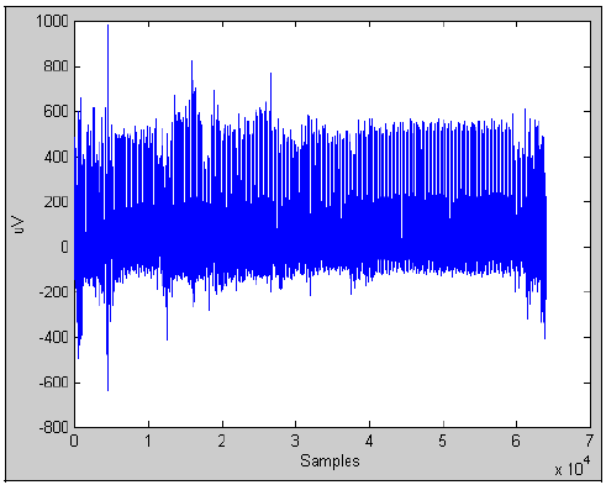

Figure 3.8: First ECG artefact removal. Notice that all the points higher than 1000 μV or lower than -1000 μV are removed

- R peaks not detected: 18
- Total peaks detected: 244

In Figure 3.9, we show only the correctly detected R peaks. We see clearly two outliers that were not discarded by the algorithm (the mean R-R distance is 243. $\frac{3}{2} * 243 = 364,5$ which is higher than the actual length of the 2 outliers, that is why they are considered correct). Those outliers will be discarded later on by the algorithm.

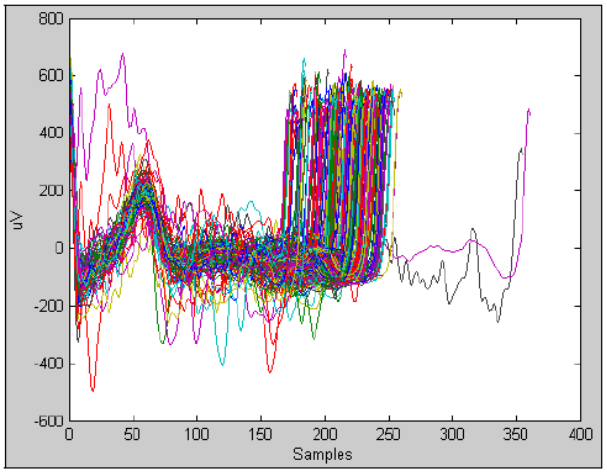

Figure 3.9: ECG waveforms that are considered correct after the first outlier detector

Besides the outliers that are much longer than the average, we also see that some ECG waveforms do not follow the average ECG waveform shape. This is why we apply a different outlier detector at this point. The ECG waveforms that have more than 3 standard deviations at any point between 1 and 120 (see Figure 3.10) are considered outliers. In other words, the ECG waveforms in Figure 3.9 that do not fit inside of Figure 3.10 (point by point) are considered outliers.

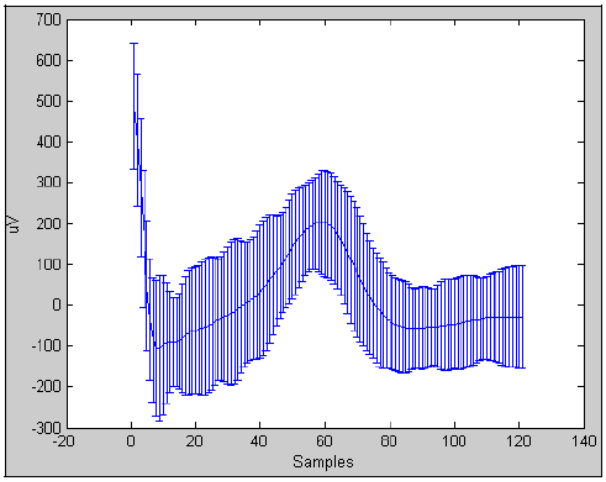

Figure 3.10: Average and error bars corresponding to 3 standard deviations of the 120 first samples of the ECG waveforms

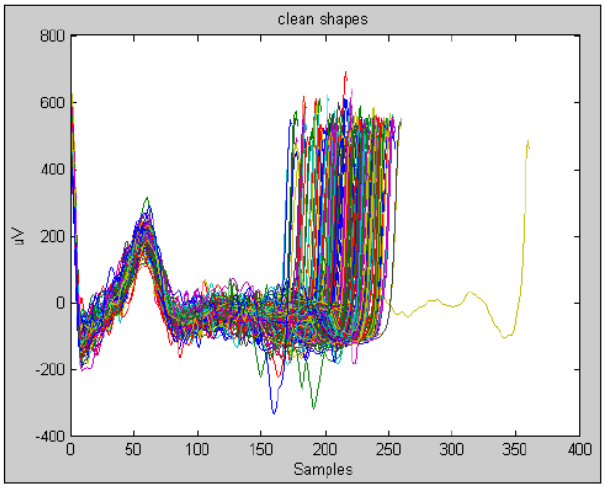

Figure 3.11: ECG waveforms that are considered correct after the second outlier detector

In Figure 3.11 we plot only the ECG waveforms that are not considered outliers. In this step and in this particular case we have discarded a total of 25 ECG waveforms. We can see in that figure that all the ECG waveforms look more or less similar, except that we have an outlier (the ECG waveform plotted in yellow which is much longer than the others because an R peak was not detected and thus the system plots two consecutive beats as if they were one) and that they do not have the same length. This is due to the fact that, in general, the duration of each heart beat is not regular. This is caused by several factors such as respiratory arrhythmia and variations of the heart beat rate. In our case, in order to make the ECG waveforms independent of the heart beat rate and in order to make them all have the same length (necessary for the classifiers) we apply the following algorithm:

- We automatically detect the end of the T complex (see Figure 3.12).
- We select the segment from the end of the T complex until 50 points away from that point (see Figure 3.12).

- We resample this segment (which is the less affected by the heart beat rate variations) in order to end up with ECG waveforms of a fixed length of 75 samples (Figure 3.13).

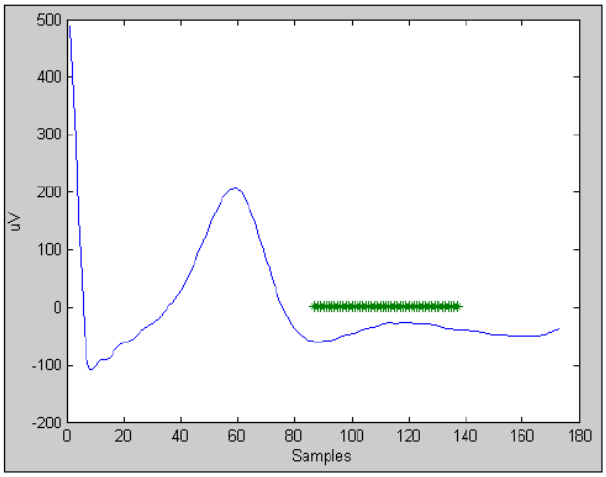

Figure 3.12: Mean of all the ECG waveforms of fig. 3.11 (from sample 0 to the last sample of the shortest ECG waveform). The green segment represents the part that is going to be resampled

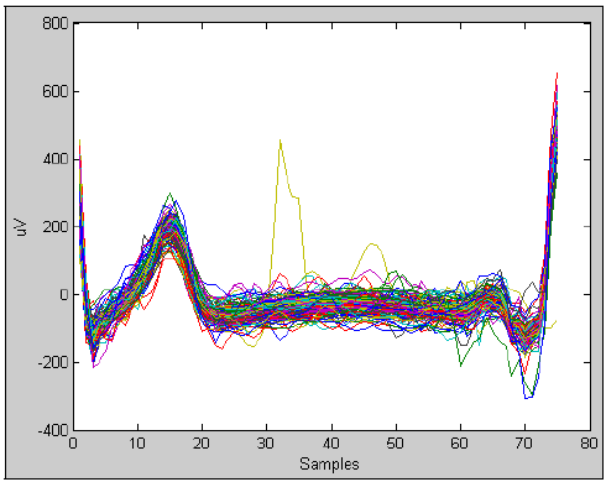

Figure 3.13: ECG waveforms after the resampling (normalisation)

In Figure 3.13 we can see the resampled (or normalised) ECG waveforms. We notice that the P complex appears around sample 65. Before it could not be seen because the length of the ECG waveforms was not the same, and thus it was occluded. We can also notice that the yellow ECG waveform, which is the same outlier we had in Figure 3.11, is now set at the same length as the others, and thus the peak that was not detected appears now clearly visible in the middle of the figure. In order to discard this ECG waveform and other possible outliers we apply the same methodology than before (see Figure 3.10), but in this case we use all the samples of the ECG waveform since now they have the same length.

After removing all the ECG waveforms that do not fit point by point in Figure 3.14, we obtain the final ECG waveforms that can be seen plotted in Figure 3.15. Those waveforms are the ones that will be used as features.

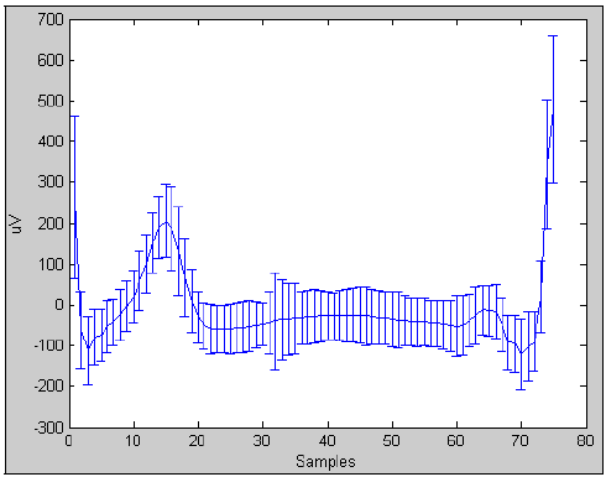

Figure 3.14: Average and error bars corresponding to 3 standard deviations of the ECG waveforms

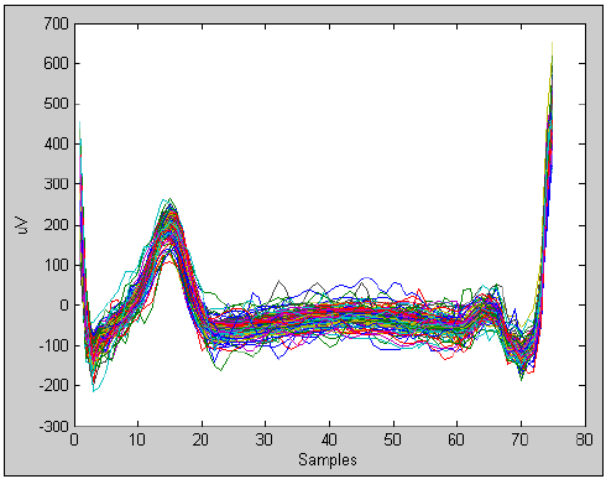

Figure 3.15: ECG waveforms considered correct after the third outlier detector

3.4 Results

In this section we will summarise the results of the different biometric system we have developed. These results can be found in the paper Riera et al. [33] included in section B and also in the book chapters included in annex C and D.

In the publication (Riera et al. [33]), we only worked with EEG and we followed a strict protocol in which the subjects had to sit down and close their eyes in order to avoid movement and ocular artefacts. The recording time was set to 1 minute. Often, in biometric systems the performance is given in terms of the Equal Error Rate (EER). The EER is defined in terms of True Acceptance Rate (TAR) and False Acceptance Rate (FAR). The TAR is the percentage given by the number of positive legal transactions divided by the total number of legal transactions. By legal transaction we mean that an enrolled subject claims his true identity while performing the biometric test, and by positive we mean that the biometric system correctly authenticates the subject. The FAR is the percentage given by the number of positive illegal transactions divided by the total number of illegal transactions. It is obvious

that for a perfect biometric system, the TAR should be 100% and the FAR should be 0%. As this situation is very hard to achieve for any biometric system, in general we are interested in keeping the TAR as high as possible while keeping the FAR as small as possible. The EER provides the performance as a compromise between those two values. Basically the EER is equal to the FAR when the FAR is equal to 100-TAR.

Another way to understand the terms TAR and FAR is using the Confusion Matrix (Kohavi and Provost [43]), presented in table 3.2 for a 2-class classification problem. The confusion matrix summarises the information about the actual and predicted classifications done by a classification system.

		Predicted	
		Rejected	Accepted
Actual	illegal	a	b
	legal	c	d

Table 3.2: Confusion Matrix

The meaning of the entries in the confusion matrix depicted in table 3.2 have the following meaning:

- a is the number of correct predictions that an instance (i.e. transaction) is negative (i.e. illegal)
- b is the number of incorrect predictions that an instance is positive (i.e. legal)
- c is the number of incorrect of predictions that an instance is negative
- d is the number of correct predictions that an instance is positive

From the above values we can define the TAR, FAR and also the True Rejection Rate (TRR) and the False Rejection Rate (FRR) as follows:

$$TAR = \frac{d}{c+d} \tag{3.1}$$

$$FAR = \frac{b}{a+b} \tag{3.2}$$

$$TRR = \frac{a}{a+b} \tag{3.3}$$

$$FRR = \frac{c}{c+d} \tag{3.4}$$

From the above equations we can see that TAR+FRR=100% and that FAR+TRR=100%. A typical way to represent the FAR and the FRR is by using the so called FAR-FRR diagram, presented in figure 3.16.

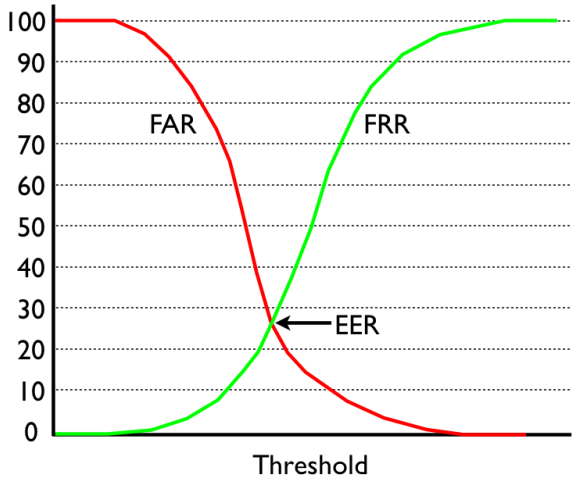

Figure 3.16: FAR-FRR diagram. The EER is given by the crossing of both curves

From figure 3.16, we can see that if we choose a low threshold, we can reach a very small FRR, but on the other hand the FAR will increase. We would have a system that would accept most of the legal users, but on the other hand, a high number of illegal users would also be accepted as legal. If we choose a higher threshold, very few illegal users would be accepted by the system, but on the other hand many legal users would not be accepted either. The EER provides the optimal compromise between the FAR and the FRR (or, which is equivalent, between FAR and TAR).

In this paper we tested our system in 2 operating modes: authentication and identification. In authentication mode, the subject undertaking the biometric test claims his identity so the system performs a one to one match (it extracts the claimed biometric signature from the database and compares with the biometric sample extracted). In identification mode, the subject does not claim his identity and the systems performs a one to many match (it compares the extracted biometric sample to all the biometric signatures stored in the database and outputs the identity of the most similar signature, if any).

In our work we reached an EER equal to 3.4% in authentication mode and 5.5% in identification mode. These values outperform the performances of other papers, as explained in the publication. It is also important to take into account that we are only using 2 frontal electrodes (Fp1 and Fp2).

In the book chapter (Riera et al. [34]) that can be found in annex C, we focused on a similar work, but we recorded a different dataset. In this research we also developed a biometric system based on EEG, and we fused the results with the ECG biometric system to provide an overall performance. It is important to take into account that with the ENOBIO recording device, we are able to record EEG and ECG simultaneously. For EEG we reached an EER equal to 20.8%. We observe a performance degradation compared to the results from (Riera et al. [33]). The main reason is that we are working with a different data set, and the recording conditions were not as strict as the ones of the previous work. Regarding ECG, we reached an EER equal to 2.1%. This is a very good result compared to State-of-the-Art biometric systems, and it was a very positive surprise for us to see that ECG works very well as a biometric trait. Actually ECG is very easy to record, and in our case we used one electrode

placed in the left wrist of the subjects, referenced to a clip electrode place in the right ear lobe. Finally in this work, we also fused the results from both biometric systems. The fusion results are summarised in table H.1.

	TAR	FAR
decision function 1	97.9%	0.82
decision function 2	100	0

Table 3.3: Final results after fusion

We see that the using the decision function 1, which is a simple line with only 2 parameters, we are able to decrease the FAR from 2.1% (the ECG FAR which is equal to the EER, as explained before) to an overall FAR of 0.82%. Using the decision function 2, which is a line with multiple corners (12 parameters), we reach a perfect performance (EER=0%). The main problem of using a decision fusion with so many parameters is that a greater generalisation error is expected when applying the same system to a different data set. In any case, we can conclude that the fusion of EEG and ECG biometric systems is quite promising.

In the book chapter (Riera et al. [31]) that can be found in annex D, we worked again with a different dataset and in this case the subjects were seated but free to move and they had their eyes open while performing the biometric test. The movements they were allowed to do were those of an office working environment such as using keyboards, using the mouse, reading, answering the phone, drinking water and so on... . This work was quite challenging since it is well know that electrophysiological recordings are very sensitive to movement artefacts (this applies to both EEG and ECG) and to ocular artefacts in the case of EEG. The results we reached for the EEG biometric system are summarised in table H.3.1.

Take	TAR	FAR (EER)
1	64%	36%
2	63%	37%
3	65%	35%

Table 3.4: Classification results of EEG (office takes) without applying the artefact correction module

As we can see the performance of the office takes shows some biometric potential, but it is not very high. The mean of the EER is 36%. Applying the artefact corrector we see that the results improve considerably as we can see in Table H.3.

Take	TAR	FAR (EER)
1	71%	29%
2	82%	18%
3	70%	30%

Table 3.5: Classification results of EEG applying the artefact correction module

We can see that the performances are a bit worse than in the results described in the previous work (Riera et al. [34]). The mean of the performance in terms of EER over the 3

takes is 25.6% and the result we reached in (Riera et al. [34]) was 20.8%. Taking into account the big movement artefacts, we consider this result as positive, since they are comparable.

The results of the ECG biometric system in the same conditions are presented in the following table.

Take	TAR	FAR (EER)
1	87%	13%
2	88%	12%
3	88%	12%

Table 3.6: Classification results of ECG biometric modality in the office takes

Again, there is a performance degradation compared to the previous presented work. The mean performance over the 3 takes of the current ECG biometric system is 12.3% compared to the EER equal to 2.1% we reached before. In any case, taking into account the recording conditions, we consider this result promising.

In this work we also present some preliminary results of two novel biometric systems. One is based on EOG and the other is based on EMG. With EOG we reached a classification rate (CR) of 24.6% (as we have 23 subjects, a random classification would provide a CR equal to 4.3%). It is important to note that the EOG was collected using the frontal electrodes (Fp1 and Fp2) used for the EEG recording. Although this result is not very promising, we considered it interesting enough to present it, and as far as we know, no biometric system has been implemented using EOG. Moreover, a biometric system based on EOG and blink patterns could improve the performance of our EEG biometric system since EOG and EEG can be recorded with the same electrodes in our case (remember we use frontal electrodes where EOG is easily picked up). Finally, using EMG recorded with two bipolar set ups (each one placed in each forearm) while the subjects were keystroking, we reached a very promising result: CR equal to 95.6%. In this case no machine learning or classification techniques were applied. We just plotted our features and classified by doing subjective clusters. In any case, the potential of the use of EMG as a biometric tool has been demonstrated in this work and, as far as we know, EMG has not been applied before as a biometric trait.

In the paper (Soria-Frisch et al. [36]) included in annex F, we present our work in fusion techniques applied to this data set. Several fusion operators were tested, including Power Mean, Yager S-Norm, Weighted Sum, Uninorm based on Yager Norms and Ordered Weighted Averaging. The results of this paper shows that appropriate fusion techniques can significantly improve the results of the final biometric score.

3.5 Conclusion

The potential use of ECG as a biometric trait has been proved in this chapter. EEG has also been proved a robust biometric trait, but not as much as ECG. In any case, it is very interesting to see that certain features extracted from EEG are quite stable over time (the inter-subject variability is low) and quite different among subjects (high intra-subject variability). From

a biological perspective, this fact should not seem very surprising: the brain has about 10^{11} neurones and about 10^{15} synapses. It is very unlikely that two brains are identical. But the proper question here is, are we able to distinguish through EEG, the differences among brains? The purpose of this work was to find suitable features extracted from EEG to find differences between brains, and we also showed a potential application in the field of biometrics. We also wanted to use few electrodes (in our case 2 frontal electrodes) to make the application unobtrusive and suitable for out-of-the lab environments. It is interesting to note that in the very fast growing field of Brain Computer Interfaces (BCI), researchers often look for EEG features that are similar between subject in order to decrease or even suppress the training time of such systems. In our study, we did exactly the opposite. As a reminder, and after testing a lot of different features, the ones we used in this work are: Fourier Transform, Autoregression Coefficients, Mutual Information, Correlation and Coherence.

Such a biometric system can be used for certain applications, where security is very important and it is worth it to spend some time to undertake the biometric test. One advantage of an EEG based biometric system is the universality (every living person has a working brain) and that it is very hard to spoof. We think that in the future, where such systems will be more likely to be used, many other application could be done, based on a similar system. For instance, it would be very interesting to use such systems in Virtual Environments (VE). In such a scenario, where users are represented by avatars that could be impersonating other identities, this system could be authenticating the users in a continuos manner and thus increase trust in sensitive transactions. This is further explained in the annex E where we included our work on those issues (Riera and Dunne [35]). Another very interesting application that could be developed with a very similar system is emotion detection. Many works have been published regarding emotion detection based on EEG (Zhang and Lee [44], Petrantonakis and Hadjileontiadis [45], Chanel et al. [46], Aftanas et al. [47], Aftanas et al. [48], Coan and Allen [49], Flores-Gutiérrez et al. [50]), for mental workload measurement based on EEG (Berka et al. [51]), and also stress detection based on EEG (Gaylord et al. [52], Lewis et al. [53], Sherlin et al. [54], Kemp et al. [55], Riera et al. [56]). Any of those systems could apply our algorithms to detect the identity (identification mode) of the users or to authenticate them (authentication mode). That would provide an added value to these systems. Another application very much used nowadays are the BCI's. In those systems, in a similar manner, the user could be authenticated (or identified) automatically by the computer and the BCI session would be automatically personalised for each single user. Moreover, in the book chapter (Riera et al. [31]) that can be found in annex D, we describe a novel concept: a BCI system applied to biometrics. The main idea is that if we are able to personalise a BCI system for each single user, we can use it to input a password in the computer to unlock it, by controlling the direction of a moving ball on the screen. In such a system, we can find 3 levels of security:

1. Each subject would choose their own imaginary movements (tongue, left hand, right hand, left foot, right foot, both hands or both feet, for instance), and its selection would only be known by him.

2. Each subject would perform a training session in which the best suited features for each user would be automatically selected

3. The password itself that would only be known by each user.

We have also demonstrated the potential use of ECG for biometric purposes. As we have seen, ECG is a very robust biometric trait and its reliability is quite high. Using similar arguments as the ones above for the uniqueness of brains, it is not surprising that each heart provides a unique electric signal, and thus suitable for biometric purposes. One good advantage of ECG compared to EEG is that its signal is easier to record, mainly because of two reasons: its amplitude is much higher (about 1 mV while EEG is about 50 μV) and in our case we only used one electrode placed in the left wrist referenced to a clip electrode in the right ear. The left wrist electrode could be embedded in a bracelet and the reference could be certainly placed in other places (in the right hand wrist for instance). Many commercial wearable ECG recording systems are available and many researchers are working on prototypes (an example of stress studies based on ECG can be found in Salahuddin and Kim [57]). As in the case of EEG, ECG is also used in VE in order to extract objective real time information of the users. There are interesting correlations between ECG features and emotions. This information could be used by the VE in order to change according to the emotion of the subject (for instance as a simple illustrative example we can think that if the heart beat rate increases, make the VE calmer to relax the user). If ECG is available in the VE, we could use this signal for biometric purposes, as explained above with EEG. Moreover, ECG recording systems are in general more portable and wearable, so the signal could be used in a continuos manner for authentication/identification purposes. These ideas are very common in the rapidly growing field of pervasive computing.

Fusion techniques have been applied in our work with EEG and ECG. The fusion algorithms are very powerful and very useful in many fields, particularly in biometrics. If a subject undertakes several biometric tests, and supposing the different biometrics traits are independent, even if each individual biometric test has a poor performance, the fusion of several biometrics can provide a very reliable final score. As we have seen with EEG and ECG, applying simple fusion techniques, we were able to reach a perfect classification. We have also worked on more complex fusion techniques in the paper (Soria-Frisch et al. [36]) included in annex F.

Finally in this chapter we have also demonstrated the potential use of EMG as a biometric technique. In our work with EMG, we only provided a proof of concept but with very promising results. As in the case of ECG, the EMG signal is easy to pick up (the amplitude goes up to 10 mV) and the sensor to record it could be made in a very wearable manner, embedded in a bracelet or in elastic bands, for instance. In that sense we could have another biometric source of information, which could be used in a continuous manner. We insist that as far as we know, no other study of EMG based biometric systems has been presented before. Our work on EOG applied to biometrics has been presented for its novelty, but even though the performance is not very high, a certain biometric potential was also found.

Chapter 4

EEG characteristics in First Psychotic Episode Patients

In this chapter we present our work on EEG data analysis applied to First Psychotic Episode (FPE) data. The aim of this study is to find discriminative features in the EEG data of SZ subjects. After the introduction (4.1), we present a description of the data set (4.2). We then outline the main steps of the data analysis (4.3), the main results (4.4) and finally the conclusions (4.5).

4.1 Introduction

The EEG signal is easy to record, the equipment is relatively cheap and moreover it is unobtrusive. Those are very important advantages over other equipment used to record brain signals. Of course it also has some drawbacks, such as the spatial resolution, if we compare with Functional Magnetic Resonance Imaging (fMRI). On the other hand the time resolution is very high, i.e. same time scale as the firing of the neurones. We can find other systems that record brain activity with a higher spatial accuracy such as ECoG and deep brain electrodes, but in this case, they are invasive.

Because of these reasons, the viability of performing diagnosis based on EEG would yield a big interest in the clinical community. Of course this task is not simple at all, and that is probably the reason why EEG is rarely used as a diagnosis tool (it is used in epilepsy and in sleep staging, since the patterns detected with EEG in these cases are quite characteristic). The idea behind this chapter is to apply machine learning and computational intelligence techniques to the record and process EEG data in order to unveil the potential of its use for diagnostic purposes.

Nowadays, the EEG is more used in detecting unusual patterns in the EEG signal rather than as a diagnostic tool per se. It is widely used in epilepsy detection (Smith [58], Silva et al. [59]) and in sleep studies (Dement and Kleitman [60], Williams et al. [61]). In fact, the EEG is the primary way to extract the so called hypnogram. EEG has also been applied in studies with alcoholics patients (Fuentemilla et al. [62]) and in meditations studies (a nice

recent review on this topic can be found in Rubia [63]). In both cases EEG has been proven a powerful tool for brain studies.

Our work is based on the analysis of EEG signals from a set of SZ subjects against a set of healthy control subjects (CON). After the data analysis we apply Machine Learning (ML) techniques to test if an EEG recording belongs to the SZ group or if it belongs to the CON group. Such a tool would be useful as an extra source of information for the diagnosis of SZ disease. Moreover, this source of information would be objective, since the classification is done by an automatic algorithm where no human bias could exist.

There are several works that deal with diagnostic systems based on EEG, such as Dauwels et al. [64]. In this work, by extracting synchrony measures from the EEG (including correlation coefficient, mean-square and phase coherence, Granger causality, phase synchrony indices, information-theoretic divergence measures, state space based measures, and stochastic event synchrony measures) the authors are able to reach a classification rate of 83% between Mild Cognitive Impairment (MCI) and age-matched control subjects.

An interesting feature that has also been applied for diagnosis based on EEG is the Synchronisation Likelihood (SL). This technique will be largely explained in this chapter, since it is the feature we have used in our study. For instance in the work (Stam and van Dijk [65]), SL has been applied to Alzheimer Disease (AD) patients and in (Micheloyannis et al. [66]) to SZ studies. In any of these works, no ML techniques were applied. In another work (Timashev et al. [67]), the authors propose an approach that can be useful for SZ diagnosis. They use a time series analysis method called flicker-noise spectroscopy (Timashev [68]) and they are able to classify among 4 categories corresponding to different risk levels of subjects' susceptibility to SZ. Again in this case ML techniques were not applied in the classification stage.

Another recent interesting work is the one presented in (Neuhaus et al. [69]). By applying Event Related Potential (ERP) techniques and ML, they are able to reach a classification rate of 79% between SZ patients and matched controls. In this work they even go one step further in their analysis by applying source localisation techniques, particularly sLORETA (Pascual-Marqui [70]) and found dysfunctions in the anterior cingulate cortex (in the time frame of the P3 ERP component) and deficits in the right posterior current density (in the time frame of the N1 ERP component). In the work by (Oribe et al. [71]), ERP are also used to study differences between Bipolar Disorder (BD) and SZ and in the conclusions the authors claim that they are able to differentiate between both populations based on meaningful statistical differences, but no ML techniques were applied in this work and they did not work on a subject to subject basis. Another interesting paper where ML is applied to EEG is (Khodayari-Rostamabad et al. [72]). They reach a performance of 84% in the prediction of the efficacy of the treatment of SZ with clozapine.

SZ has been explained in terms of disrupted functional connectivity between different brain regions (Andreasen et al. [73], Friston [74]), and this can be considered a well established hypothesis in the SZ literature. A good review of this "disconnection hypothesis" can be found in Schmitt et al. [75]. The authors describe several techniques to study the disconnectivity between different cortical areas. For instance, Magnetic Resonance Imaging (MRI) and postmortem investigations revealed deficits in the temporoprefrontal neuronal circuit. Others tools, with high temporal resolution, used in this review are Transcranial Magnetic Stimulation

(TMS), electroencephalography (EEG), and magnetoencephalography (MEG). The "disconnection hypothesis" has been also studied in AD, for instance in the work (de Haan et al. [76]). Another general work that studies functional network disruption in the degenerative dementias can be found in (Pievani et al. [77]).

A very powerful analysis tool that has been largely applied to study such disrupted functional connectivity is the so called graph theory. Basically, this mathematical technique considers brain regions in the case of fMRI studies (Supekar et al. [78], Liu et al. [79], Achard and Bullmore [80], Bassett et al. [81], Guye et al. [82]) or electrodes in the case of EEG or MEG (Rubinov et al. [83], Jalili et al. [84], de Haan et al. [76]) as nodes of an abstract graph, and applies graph analysis techniques to study the relations between those nodes and in that way understand the properties of the overall graph. For instance there are several works that study the small world property of the brain (Bassett and Bullmore [85], Reijneveld et al. [86]). In this second work, the authors demonstrate through evidence from computational studies, in vivo experiments, and functional MRI, EEG and MEG studies in humans, that both the functional and anatomical connectivity of the healthy brain have many features of a small world network. The small world network property can be understood as a graph showing that the average distance between pairs of typical nodes is small while the graph still has a high degree of clustering. Many different abstract graphs, such as the World Wide Web, gene networks and social networks, all exhibits small world network properties. A deep review of these techniques applied to fMRI, EEG and MEG can be found in (Bassett and Bullmore [87]) and a good introduction of the basic principles of graph theory can be found in (Bullmore and Sporns [88]). A recent paper that describes the uses and interpretations of complex networks measures applied to brain connectivity can be found in (Rubinov and Sporns [89]).

There is also evidence that show that some types of oscillations of the brain, in particular in the Gamma band, are impaired in SZ (Minzenberg et al. [90]). A good review of this can be found in (Sun et al. [91]). In this other review (Uhlhaas and Singer [92]), the author describes that the synchronisation of beta and gamma band activity is abnormal in SZ, suggesting a crucial role for dysfunctional oscillations in the generation of the cognitive deficits and other symptoms of the disorder.

FInally, neuroscience computational models have also been proposed to explain the different symptoms of schizophrenia. those symptoms are often classified as cognitive (distractibility, working memory deficits and/or poor attention), positive (delusions, paranoia, and hallucinations) and negative (apathy, lack of spontaneity, motor retardation, disturbance of volition, blunted affect and emotional withdrawal). A nice review can be found in Rolls et al. [93]. As a summary, the computational models are built using both theoretical and experimental results. By running simulations on biologically realistic neural networks, schizophrenia can be understood in relation to noise and signal-to-noise ratio of these networks. More over, these simulations have shown that the functioning of NMDA (N-methyl-d-aspartate), GABA (g-aminobutyric acid) and dopamine receptors are connected to the concepts of noise and variability.

In the rest of this chapter, the analysis performed to a data set of SZ subjects will be explained in detail.

4.2 Data Set Description

Data was collected to a number of subjects that came to the Hospital de Badalona (Fundación Benito-Meni) while suffering a First Psychotic Episode (FPE). One of the main interests of this data is that an EEG was recorded while the subjects were having the psychotic episode and before taking any medication.

I wish to thank Dr. Emili Rojo and Dr. Oscar Pino (Hospital de Badalona, Fundació Benito-Meni) who made possible the EEG recordings within the few hours after the admission of the patients and before the pharmacological treatment, and also provided the clinical data and the follow-up information of the patients. Also many thanks to Dr. Lluís Fuentemilla (Laboratori de Neurodinàmica de la Universitat de Barcelona) who was the principal responsible of the EEG data collection of the patients in very difficult technical conditions. Also many thanks to Diego Lozano-Soldevilla (Laboratori de Neurodinàmica de la Universitat de Barcelona) for recruiting and recording a part of the control subjects needed for this study.

In this study, a total of 15 FPE subjects along with 16 matched controls participated. Regarding the FPE patients we have made a further subdivision considering their clinical evolution: 9 were later diagnosed as SZ while 6 did not match the SZ diagnostic. From the 9 subjects diagnosed as SZ, we also recorded 7 of them some weeks later after undertaking a pharmacological treatment. As we will see later on, several studies have been made with this data. In the next list we can see in a summarised manner the different subdivisions we have made in our data set:

- 15 Subjects having FPE from which:
  - 9 Subjects having that were later diagnosed as SZ, from which:
    - 9 pre (non-medicated)
    - 7 post (medicated)
  - 6 Subjects that do not fulfil the criteria to be considered SZ (nSZ).
- 16 Matched Controls (CON)

The 9 schizophrenic patients (6 males and 3 females) used in this study had an average age of 25.9 $\pm$ 4.8 years. They were all right handed except one of them. The average time between pre and post takes was 44.0 $\pm$ 26.3 days. They had an average IQ of 97.5 $\pm$ 11.3. 4 of them had their school graduates (the mandatory 10 school year diploma), 3 had their full 12 year school diploma and 2 of them a university degree. All of them were diagnosed as schizophrenics with an average Positive and Negative Syndrome Scale (PANSS) of 90.8 $\pm$ 23.8 being the lowest PANSS score equal to 66.

Regarding the medication taken between the pre and post takes, all of them were administered with antipsychotics (6 of them with Eskazine, 1 with Haloperidol, 1 with Quetiapina and 1 with Olanzapina). 4 of them also took anxiolytics (either Diacepan, Tranxilum or Paroxetina). 4 of them also took anticholinergics (Akineton). Finally, 4 of them also took sleeping pills if they suffered from insomnia (either Stilnox, Lormetazepam or Rohipnol).

Regarding the non-schizophrenics subjects used in this research (4 males and 2 females) , they had similar mean and standard deviation as the schizophrenic subjects. Once stabilised with drugs, the subjects were identified as bipolar patients, patients with isolated psychotic episodes or other alterations not compatible with a diagnosis of schizophrenia.

Finally we have also recorded EEG data to 16 matched control subjects, their mean age being 26.4 $\pm$ 4.5. A Student's t-test applied to the age of the FPE group and to the control group provides a p equal to 0.82, which proves that the age of both populations are well matched.

For each subject between 4 and 8 blocks of EEG data were recorded in a single session (average number of blocks per subject 6.6 $\pm$ 1.2). Each block lasted about 5 minutes. Actually the protocol used for these recordings was one of Mismatch Negativity (MMN) which is a well-known auditory Evoked Related Potential (ERP).

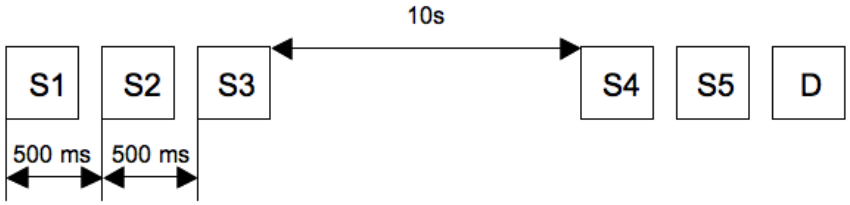

Figure 4.1: MMN protocol used in the data recording. The standard tone (S1, S2, S3, S4 and S5 in the scheme) was 25 ms long while the deviant (D) was 100 ms

In any case it is important to note that in the study described in this section, we only used spontaneous EEG data, that is, we used the epoch of data free of auditory stimuli. From the 10 seconds between the triad tones, we selected the 8 seconds in the middle by discarding the first and last second, in order to avoid long term ERP effects and expectancy effects. From each block of data, we extract 25 8-seconds epochs of spontaneous EEG. From now on we are going to work only with these epochs, discarding the ERP part of the data.

The data was recorded recorded with a Biosemi ActiveTwo EEG amplifier (Metting Van Rijn et al. [94] and Metting Van Rijn et al. [95]). 64 electrodes were recorded following the international 10-20 system electrode placement. In order to do so, we used a Biosemi EEG cap, and we also used conductive gel to facilitate the contact of the electrode with the scalp and reduce the impedance. We also recorded vertical and horizontal EOG in order to subtract it from the EEG signal to reduce the ocular artefacts. Finally all these electrodes are referenced to the nose tip, by means of a last electrode placed there with the help of a sticker. The sampling rate was set to 2048 Hz, but all the EEG recordings were decimated digitally to 1024 Hz.

What we attempted to do with this data set is to find statistically significant differences between the different classes: CON, SZ pre, SZ post and nSZ pre, and classify them in a later stage.

4.3 First Psychotic Episode Data Analysis

In this section, the data analysis performed is described in detail.

As a first step we have tested the same features we used in the Biometric section 3, but we did not find any discriminative power between the different classes. Just as a reminder those features were Fourier Transform, Autoregression Coefficients, Coherence, Correlation and Mutual Information. The 3 last features, as they represent some type of correlation between 2 channels, were computed for each possible pair of channels (in that case we have 64). The number of possible combinations is 64*63/2=2016.

In a second approach, we have used the Synchronisation Likelihood (SL) feature. Actually this feature has been used before in diagnosis based on EEG of Alzheimer patients (Stam and van Dijk [65]) and in SZ studies (Micheloyannis et al. [66]). It has also been applied to study the genetic components of functional connectivity in the brain in (Posthuma et al. [96]). In this work, the authors describe that the SL is highly heritable (between 41 and 67%). SL is a powerful tool to investigate the relation between pairs of channel or more generally the relation between different brain regions. Coherence has been widely used in the analysis of the EEG signals to study the 'disconnection hypothesis'. The major advantage of using SL rather than Coherence is that the former is sensitive to non-linear dynamical interdependencies, and in recent years, evidence has been reported that the EEG signal contains weak but significant nonlinear properties and interdependencies among pairs of channels (Breakspear et al. [97]).

The methodology to extract the SL is extensively explained in (Stam and van Dijk [65] and Montez et al. [98]). Intuitively, the SL between two time series (X and Y) is a measure of synchronisation of both series. For a driver system X and a response system Y, if X is in the same state at times i and j and if Y is also in the same state at the same times i and j, then the SL between X and Y is high. In order to define a similarity between the state of X at times i and j, we use a lag and an embedding dimension, and then compute the Euclidean distance between both vectors that represent the states of X at times i and j. The same is done with the different states of Y at the same times i and j. If the distance between the state of X at time i and the state of X at time j is smaller than a certain threshold, we consider a hit for X. We define a hit for Y in a similar way. The SL is defined as the probability (over the valid j's) that there is a hit with respect to Y, given that there is a hit with respect to X. j depends on the lag and on the embedding dimension.[1]

4.3.1 Ocular Artefact Correction

This section explains an artefact correction method called GMCturbo based on GMC, implemented by Iván Cester from Starlab Barcelona and used in (Damousis et al. [99]). While GMC was using an extensive search, this new method finds the optimal parameters analytically, so the computational time improves enormously. Besides this method has a real time capacity (actually GMC methods has the same capacity, but the computational time needed to find the optimal parameters is much longer).

For this method to work we assume we have 2 EOG channels (Vertical and Horizontal) and 1 EEG channel, which we want to correct from the EOG artefacts. Of course, a simplified version of this method could be used if only 1 EOG channel is available.

In the following lines we present a brief explanation of the GMCturbo artefact corrector.

[1] I wish to thank Dr. C.J. Stam, full professor of clinical neurophysiology at the department of clinical neurophysiology of the VU University Medical Hospital in Amsterdam, for his kind advice and help regarding the use of the synchronisation likelihood measure

- The signal of the blinks and the eyes movements is several orders of magnitude higher than the EEG signal.
- The signal of the blinks and the eyes movements is much higher in EOG electrodes than in the ones used for EEG recording.

When we have few electrodes, the Independent Component Analysis (ICA) method (widely used in EOG artefact detection) has a poor performance. So, in our case, we will subtract directly a percentage of the EOG signals to the EEG signal we want to clean. Let's define:

- $\vec{S}$=EEG signal we want to correct
- $\vec{V}$=Vertical EOG signal
- $\vec{H}$=Horizontal EOG signal

Our hypothesis is that the corrected EEG signal $\vec{S_{cor}}$ looks like:

$$\vec{S_{cor}} = \vec{S} - k_1\vec{V} - k_2\vec{H} \tag{4.1}$$

As EOG signals are larger in amplitude than EEG, $\vec{S_{cor}}$ will have less standard deviation than S. So, what we want to do is to minimise the following expression as a function of k_1 and k_2:

$$f(k_1, k_2) = (\vec{S} - k_1\vec{V} - k_2\vec{H})^2 \tag{4.2}$$

In order to minimize with respect to k_1, we do the partial derivative:

$$\frac{\delta f(k_1, k_2)}{\delta k_1} = 2(\vec{S} - k_1\vec{V} - k_2\vec{H})(-\vec{V}) \tag{4.3}$$

The same for k_2:

$$\frac{\delta f(k_1, k_2)}{\delta k_2} = 2(\vec{S} - k_1\vec{V} - k_2\vec{H})(-\vec{H}) \tag{4.4}$$

Now we have to make both equations equal to zero and we will end up with a deterministic system of 2 equation and 2 variables:

$$\begin{aligned} 2(\vec{S} - k_1\vec{V} - k_2\vec{H})(-\vec{V}) &= 0 \\ k_1|\vec{V}|^2 + k_2\vec{H}\cdot\vec{V} &= \vec{V}\cdot\vec{S} \end{aligned} \tag{4.5}$$

$$\begin{aligned} 2(\vec{S} - k_1\vec{V} - k_2\vec{H})(-\vec{H}) &= 0 \\ k_1\vec{H}\cdot\vec{V} + k_2|\vec{H}|^2 &= \vec{H}\cdot\vec{S} \end{aligned} \tag{4.6}$$

We have to solve this system for k_1 and k_2. In order to do so, we can write equations 4.5 and 4.6 in a matrix form:

$$\begin{pmatrix} |\vec{V}|^2 & \vec{H}\cdot\vec{V} \\ \vec{H}\cdot\vec{V} & |\vec{H}|^2 \end{pmatrix} \begin{pmatrix} k_1 \\ k_2 \end{pmatrix} = \begin{pmatrix} \vec{V}\cdot\vec{S} \\ \vec{H}\cdot\vec{S} \end{pmatrix} \tag{4.7}$$

The solution is analytical and can be written as:

$$\begin{pmatrix} k_1 \\ k_2 \end{pmatrix} = \begin{pmatrix} |\vec{V}|^2 & \vec{H}\cdot\vec{V} \\ \vec{H}\cdot\vec{V} & |\vec{H}|^2 \end{pmatrix}^{-1} \begin{pmatrix} \vec{V}\cdot\vec{S} \\ \vec{H}\cdot\vec{S} \end{pmatrix} \tag{4.8}$$

Developing the precedent expression we have:

$$\begin{pmatrix} k_1 \\ k_2 \end{pmatrix} = \frac{1}{|\vec{V}|^2|\vec{H}|^2 - (\vec{H}\cdot\vec{V})^2} \begin{pmatrix} |\vec{H}|^2 & -\vec{H}\cdot\vec{V} \\ -\vec{H}\cdot\vec{V} & |\vec{V}|^2 \end{pmatrix} \begin{pmatrix} \vec{V}\cdot\vec{S} \\ \vec{H}\cdot\vec{S} \end{pmatrix} \tag{4.9}$$

Now we can compute both k_1 and k_2:

$$k_1 = \frac{|\vec{H}|^2(\vec{V}\cdot\vec{S}) - (\vec{H}\cdot\vec{V})(\vec{H}\cdot\vec{S})}{|\vec{V}|^2|\vec{H}|^2 - (\vec{H}\cdot\vec{V})^2} \tag{4.10}$$

$$k_2 = \frac{|\vec{V}|^2(\vec{H}\cdot\vec{S}) - (\vec{H}\cdot\vec{V})(\vec{V}\cdot\vec{S})}{|\vec{V}|^2|\vec{H}|^2 - (\vec{H}\cdot\vec{V})^2} \tag{4.11}$$

Once k_1 and k_2 are found, let's say, in a calibration phase prior the data recording, we can apply this method to correct the EEG signal from EOG artefacts in a real time manner. Let's now test this algorithm.

We can see in 4.2 that the algorithm performs very well. The blink artefact is completely removed while the rest of the EEG signal seems really similar to the raw one.

The parameters k_1 and k_2 are very similar to the ones found by the original GMC algorithm but the computational time is now about 2000 times lower. This method works quite well as it can be seen in Figure 1. Besides, it really improves the computational speed compared to the original GMC(about 2000 times faster). It would be very easy to apply it in real time for certain applications where the EOG data is available (at least one channel).

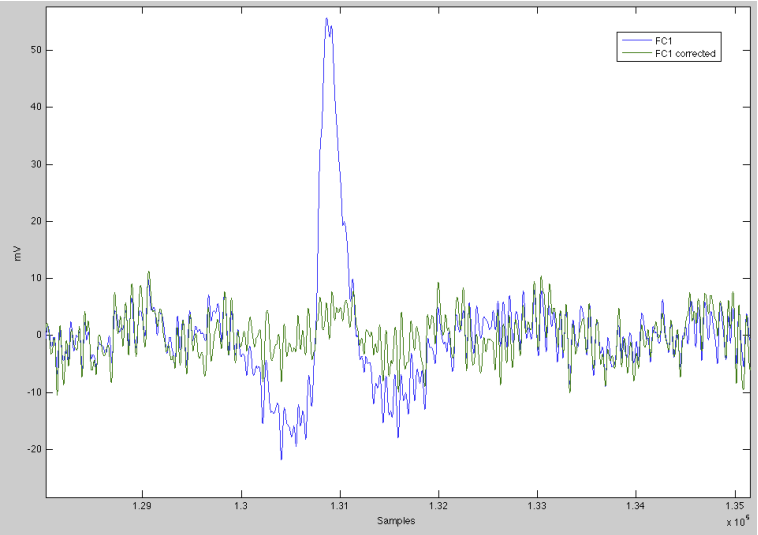

Figure 4.2: FC1 channel corrected from EOG artefacts vs raw FC1 channel. Sampling rate = 1024 Hz

4.3.2 Feature Extraction

Once we have removed the EOG artefacts from all the EEG channels, we are ready to begin with our processing methodology. Our analysis will be performed in 6 different Frequency Bands (FBs):

- Theta: 4-8 Hz
- Alpha1: 8-10 Hz
- Alpha2: 10-13 Hz
- Beta: 13-30 Hz
- Gamma1: 30-45 Hz
- Gamma2: 55-90 Hz

We therefore filter the EOG corrected EEG signals on the aforementioned FBs. Please note that we have defined Gamma2 band between 55 and 90 Hz. This is done in order to avoid the 50 Hz line noise filter often present in electrophysiological signals. At this stage we compute the SL between all the channels for all the different epochs (25) for each block of each subject. It is worth mentioning that this processing is computationally very demanding since we have to compute the SL (64*63/2)*25*#blocks*#subjects $\approx 10^7$ times.

At this point we can build a SL connectivity matrix as shown in table 4.1. We see that the SL of one channel with itself does not make sense (it would be maximal in all cases) and it is also worth mentioning that this matrix is symmetric, i.e. the SL between ch1 and ch2 is equal to the SL between ch2 and ch1. With this matrix we can now build a graph. A graph is a powerful mathematical tool useful to study and represent the interaction of certain data

-	ch1	ch2	ch3	...	ch64
ch1	X	-	-	...	-
ch2	-	X	-	...	-
ch3	-	-	X	...	-
...	...	...	...	...	...
ch64	-	-	-	...	X

Table 4.1: Synchronisation Likelihood Connectivity Matrix

sets. In an abstract way, we can think about a number of mathematical entities that interact between them. The entities would be represented by nodes (also called vertices) and their interactions by connections between those nodes (those interactions are also known as edges). Those interactions can be directional (node A interacts or affects node B but not the other way around) or not (node A and node B are related). A typical example is, for instance, a group of 10 people (i.e. a graph with 10 nodes) in which the connections represent if person X knows person Y or not. As we can see in Figure 4.3, person 4 only knows one person (person 5) and person 5 knows five (persons 0, 2, 3, 4 and 8). These studies have been largely applied in social science, ecology studies and internet studies. For a good introduction on graph theory please refer to (West [100]).

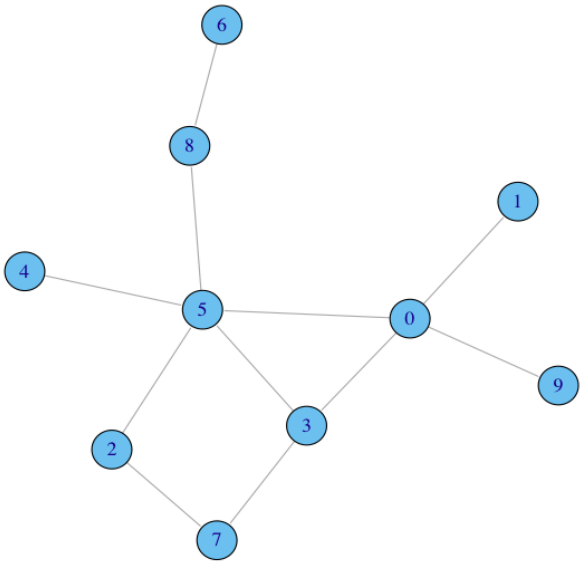

Figure 4.3: Example of a Graph with 10 vertices and 11 edges

In our case, the way the graphs are built is straightforward. For a given threshold, if SL between ch1 and ch2 is higher than that threshold, then node 1 and node 2 are connect, in the other case, node 1 and node 2 are not connected. This is done for all the possible pairs of channels. Therefore our graph will have 64 nodes. We will use different thresholds and then study how the connectivity and the path length vary as a function of that threshold. From these graphs, we will work with two common features used in complex network analysis: Cluster Coefficient (CC) and the Path Length (PL). CC is a statistical measure that represents the tendency of the nodes of a graph to cluster together. PL represents the average path length of a graph and it is computed by averaging the shortest path length between all pairs of nodes

in a graph. The transfer of information between nodes takes place faster in graphs with low PL. We have also computed the Connectivity Index (KI) which is equal to the number of connections divided by the number of nodes. The mean over subjects of this feature is represented in figures 4.25, 4.26 and 4.9 for each one of the FBs. As we can see, the evolution of KI as a function of the threshold is quite similar for each group except for the case of Gamma1 and Gamma2. But even in those FBs we can see that the behaviour of CON and SZ post groups is almost identical. For this reason the KI feature has been discarded for the rest of the data analysis.

Figures 4.4, 4.5 and 4.6 represent the mean over subjects for the First Psychotic Episode (FPE) group and for the Control group of the CC, PL and KI features plotted against the threshold. We can observe in the figures that we make the threshold vary from 0.01 to 0.4 in steps of 0.01, and thus our feature vectors have a length equal to 40. We present the plots for the Gamma1 (30-45Hz) and for the Gamma2 (55-90Hz) FBs as an example. For the rest of the FBs please refer to section 4.6. The error bars represent the standard deviation of the mean for each threshold.

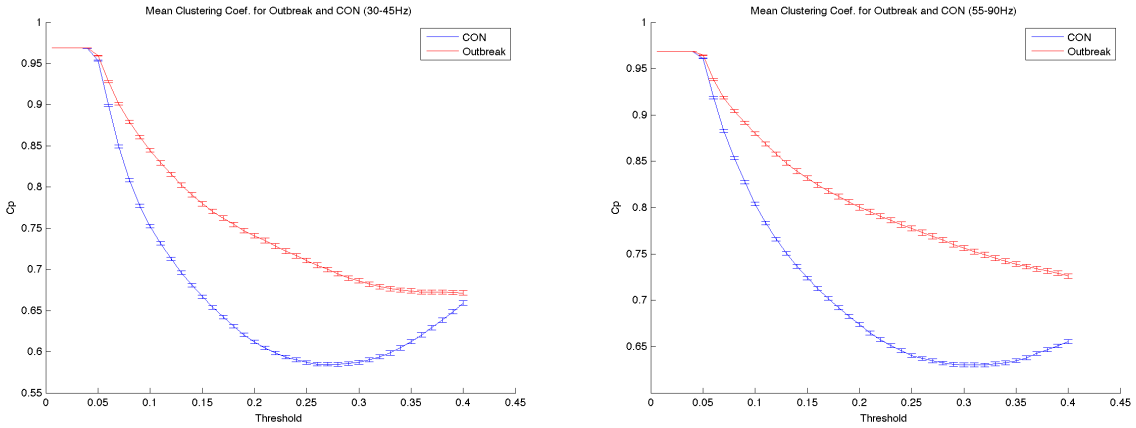

Figure 4.4: Mean over subjects of the Clustering Coefficient for 1st psychotic episode group and control group for FB 30-45Hz (left) and 55-90Hz (right)

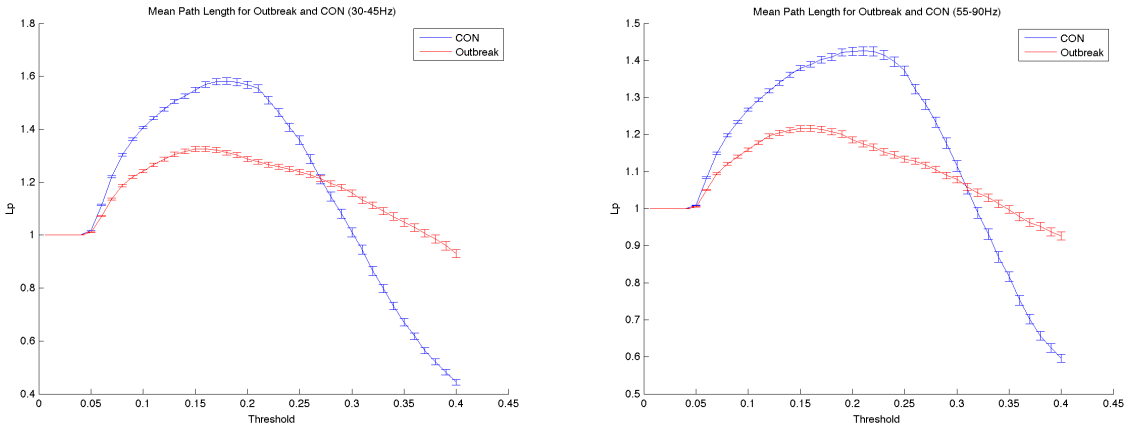

Figure 4.5: Mean over subjects of the Path Length for 1st psychotic episode group and control group for FB 30-45Hz (left) and 55-90Hz (right)

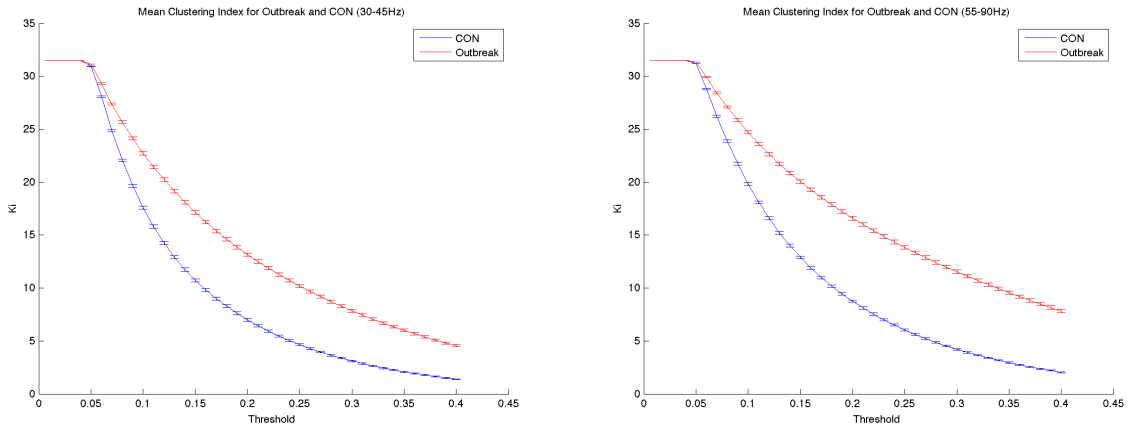

Figure 4.6: Mean over subjects of the Clustering Index for 1st psychotic episode group and control group for FB 30-45Hz (left) and 55-90Hz (right)

We can clearly see from the plots of figures 4.4, 4.5 and 4.6 that there is a clear statistical difference between the CC, PL and KI index between both populations. Our next challenge is to distinguish between each population on a subject to subject basis. This work is presented in 4.3.3.

Figures 4.7, 4.8 and 4.9 also represent the CC, PL and KI features plotted against the threshold, but in this case we have subdivided the psychotic group into its corresponding subclasses: SZ pre. SZ post and nSZ. Again, we present the plots for the Gamma1 (30-45Hz) and for the Gamma2 (55-90Hz) FBs as an example. For the rest of the FBs please refer to section 4.6. The error bars represent the standard deviation of the mean for each threshold.

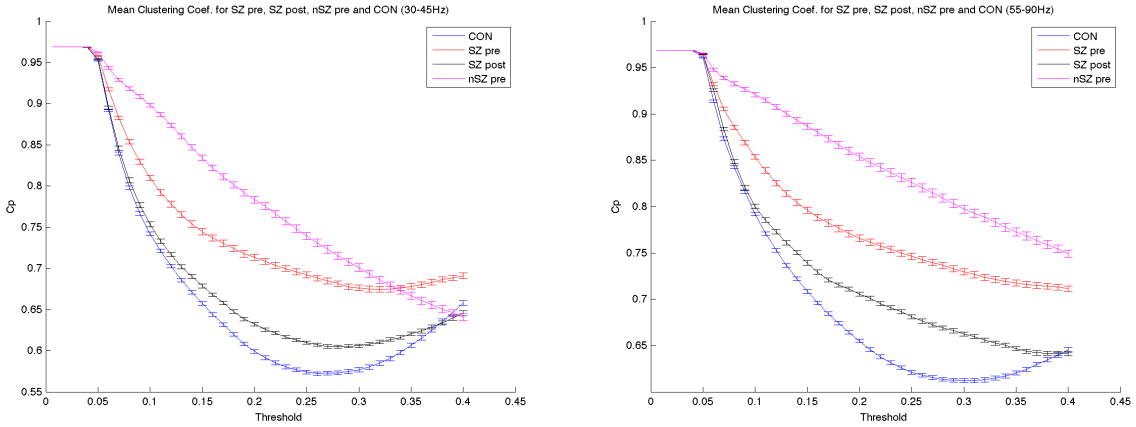

Figure 4.7: Mean over subjects of the Clustering Coefficient for each group for FB 30-45Hz (left) and 55-90Hz (right)

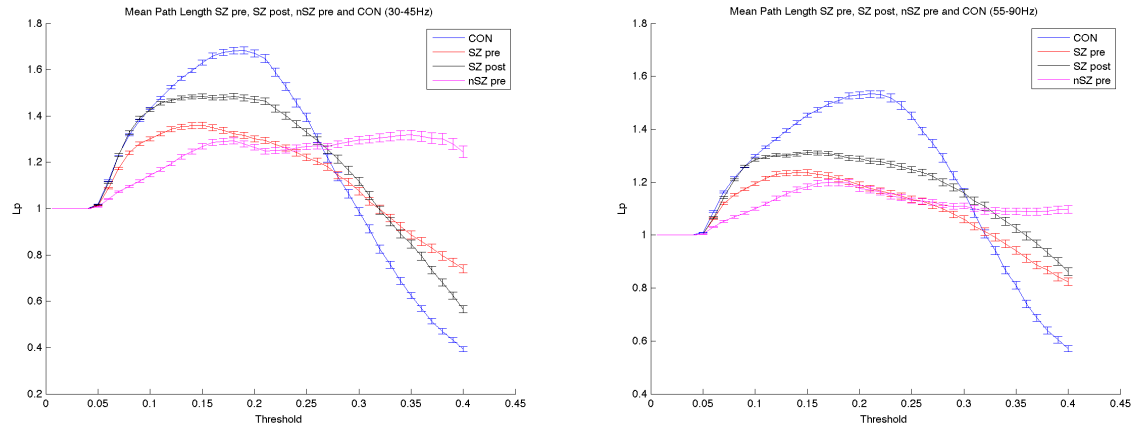

Figure 4.8: Mean over subjects of the Path Length for each group for FB 30-45Hz (left) and 55-90Hz (right)

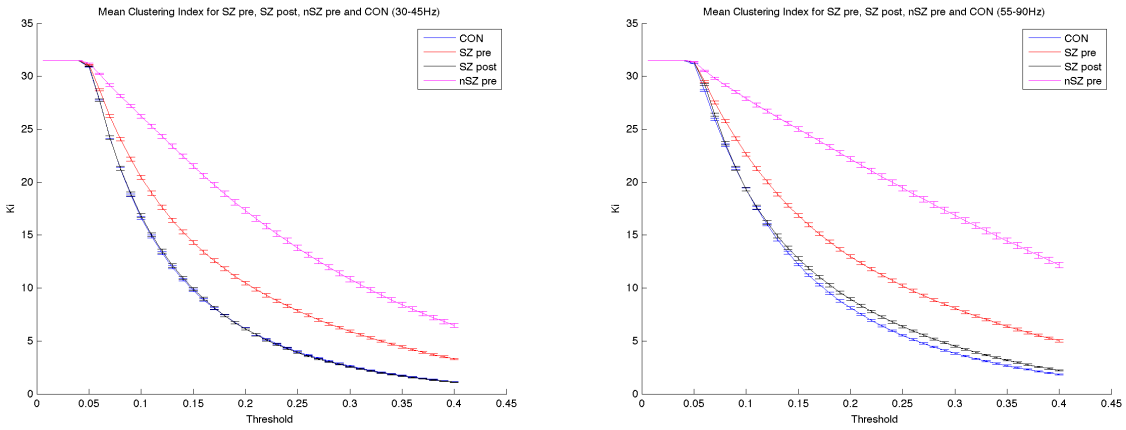

Figure 4.9: Mean over subjects of the Connectivity Index for each group for FB 30-45Hz (left) and 55-90Hz (right)

Again, we can see from the plots of figures 4.7, 4.8 and 4.9 that there are statistical differences between the CC, PL and KI index between the different populations. Our next challenge is to distinguish between each population on a subject to subject basis. This work is presented in 4.3.3.

Figure 4.10 have been included here to show graphically a concrete graph obtained for a particular threshold and a particular FB for the mean of all SZ pre and for the mean of all SZ post. Figure 4.11 represents the same for the case of CON and SZ pre. In order to draw the graph, we have placed the nodes in its corresponding scalp map: each node represents a concrete EEG channel and has been placed in its corresponding location (see Figure 4.12 to see the location standard labelling). The top is the frontal part and the bottom the occipital part of the scalp.

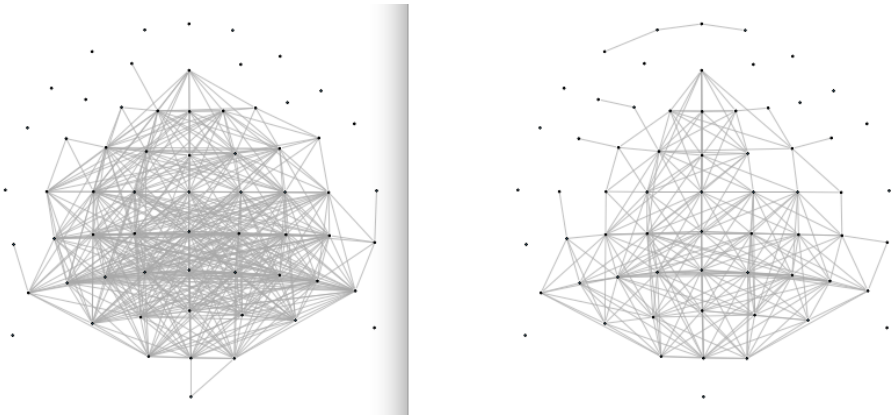

Figure 4.10: Mean over subjects of the Graph for FB 30-45Hz (Gamma1) and Threshold 0.21 for SZ pre (left) and SZ post (right)

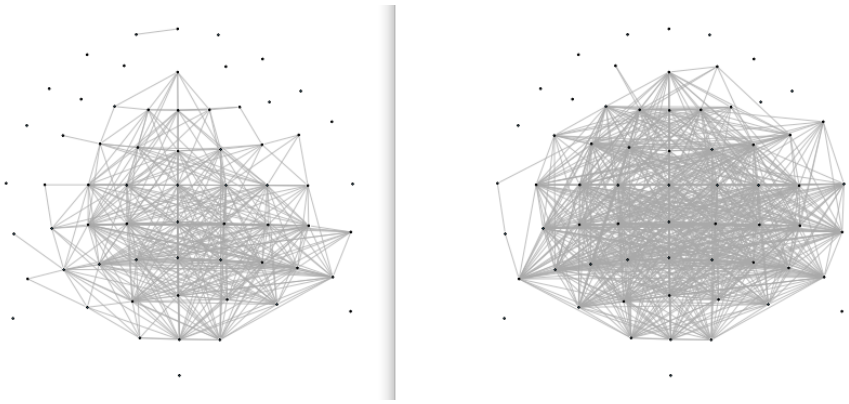

Figure 4.11: Mean over subjects of the Graph for FB 45-90Hz (Gamma1) and Threshold 0.29 for CON (left) and SZ pre (right)

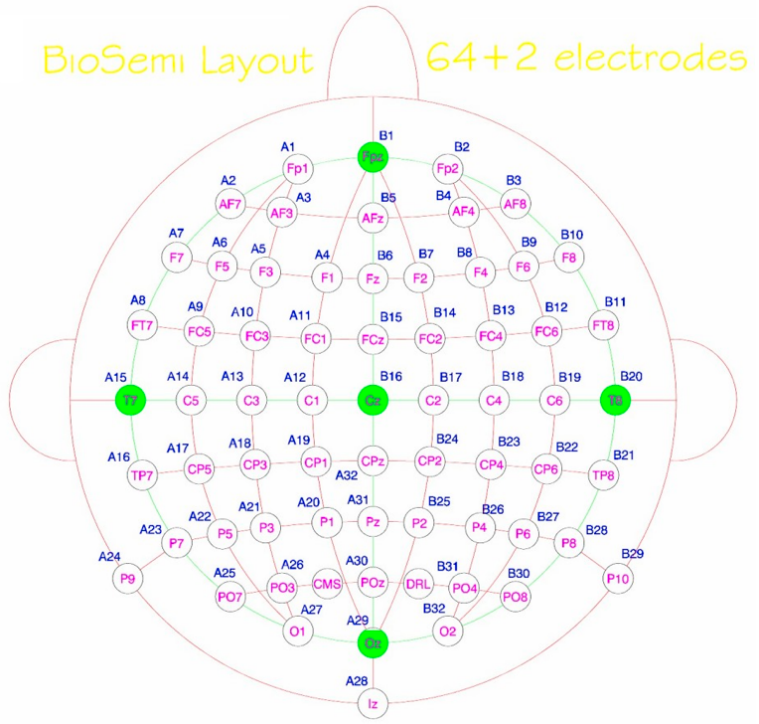

Figure 4.12: Standard 64 EEG electrodes 10-20 placement

These Figures contain interesting visual information, equivalent to the one contained in figures 4.7 and 4.7b, but represented in a different way. From Figure 4.10 we can see that for the same threshold, the group SZ pre have more connections than SZ post. The corresponding PL and CC are 1.30 and 0.71 for SZ pre and 1.45 and 0.61 for SZ post which makes sense, since in a more connected graph the PL decreases and the CC increases. From Figure 4.11 we see that the graph for the group SZ pre is more connected than the one for CON. The corresponding PL and CC are now 1.23 and 0.68 for CON and 1.12 and 0.78 for SZ Pre. As in the precedent case those results are also expected.

It is clear that there are statistical differences between the different groups. The question now is to see if, by applying computational intelligence techniques, we are able to discriminate between classes on a subject to subject basis. Such an application would be certainly very helpful for psychiatrist as an extra source of information (and moreover this source of information would be objective) in order to help them to better diagnose patients.

Let's see the methodology used to perform the classification and the way the performance of the system has been extracted.

4.3.3 Classification Methodology

To perform the classification, we have used again Fisher Discriminant Analysis (FDA), just as in our biometric works (Riera et al. [33] and Riera et al. [34]). Actually we have used FDA with 4 different Discriminant Functions (DF): Linear, Diagonal Linear, Quadratic and Diagonal Quadratic. As mentioned in the previous section 4.3.2, we have extracted 2 different features from each graph, PL and CC, each one of them with 40 components, and we did so for each one of the 6 frequency bands we used. Summarising, we have 2(features) x 40(length of each feature vector) x 6(frequency bands) x 4(DF)= 1920 potential features. In order to select the more discriminative features for our classification problem we have implemented a Genetic Algorithm (GA), in which our Fitness Function (FF), or in other words the function we want to maximise, is the classifier performance. Such performance is computed by applying a cross fold validation using the leave-one-out strategy: we keep all the features from one subject for testing and use all the rest of the features for the training. This is performed for each single subject. The Classification Rate (CR) is then computed as: number of correctly classified subjects/total number of subjects. By applying this strategy we avoid using the same data in the testing phase of the classifier and the training phase, which would results in a biased classification. Moreover, we are able to take as much profit of the available data since all subjects are used in the testing phase, and thus the extracted performance is more meaningful from a statistical point of view.

The GA is implemented by coding a 45 component binary vector. The first 40 components represent the selected thresholds (remember the length of our feature vector is 40). The next 2 binary components represent the DF used (remember we have 4) and finally the last 3 binary components represent the different FBs (remember we have 6). By applying a standard GA with an initial population size of 100 and a crossover fraction of 0.8, we select on the one hand the best PL features and on the other hand the best CC features.

In figure 4.13 we can see an example of the evolution of some parameters of the GA for the case of the classification problem SZ pre vs nSZ pre for the CC feature.

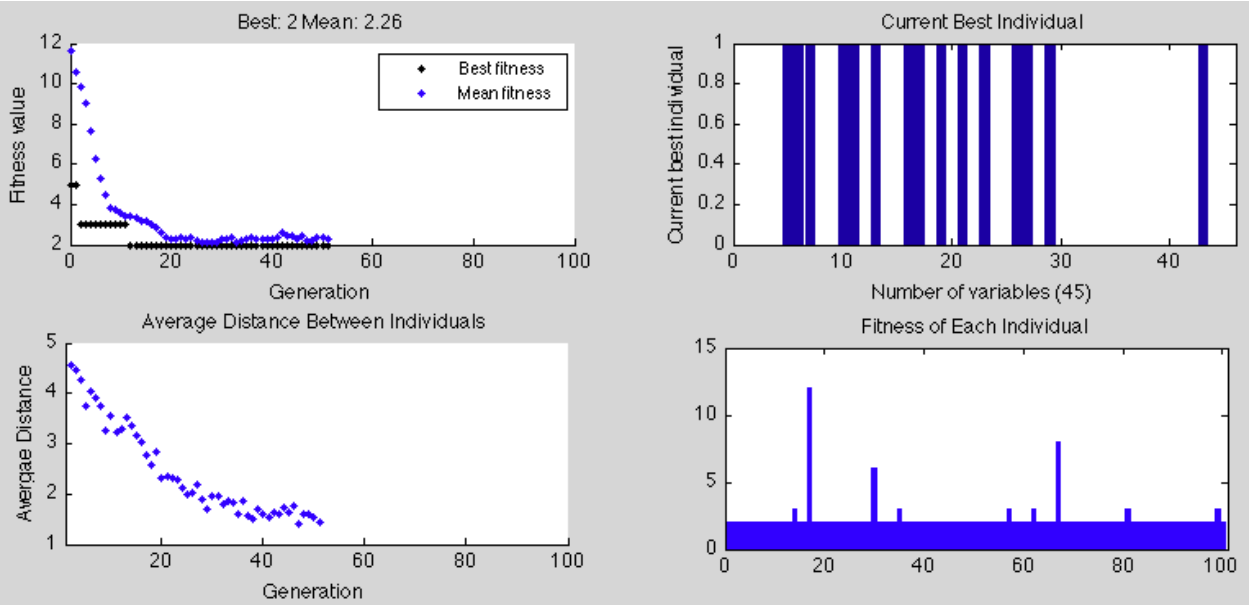

Figure 4.13: Example of the evolution of the Genetic Algorithm applied for feature selection

In the upper left figure 4.13 we can see the evolution of the mean Fitness Value (FV) and the best FV as a function of the generation number. In this particular problem the maximum of the FF is 12 since we are using 6 SZ pre patients and 6 nSZ pre patients. That would mean that our classifier did not classify any one of those patients in the right class. The minimum of the FF is 0, and that would mean our classifier correctly classified all the 12 subjects. Obviously, we are interested in finding a gene (i.e. a feature vector) that minimises the FF. As we can see in the plot, we reach a FV equal to 2 (10 out of 12 subjects are correctly classified). It is interesting to see the evolution of both parameters: the best gene in the first generation reaches a value of 5, in the third generation the GA finds a better gene with a FV equal to 3 and around generation 12, the best gene provides a FV equal to 2. In the next generations, no other gene is found to provide a lower FV. On the other hand, the mean FV is almost 12 in the first generation, but that value rapidly decreases until generation 20 where the value stays more or less constant slightly above 2. This is a typical result from GAs: in the first generation few genes are 'good' in the sense that they provide a low FV and in the next generations more and more genes becomes 'good' and thus the overall FV decreases.

In the upper right figure 4.13, we can see the best individual (also called gene) of the current generation (this plot is modified in each generation). As we can see, it is a 45 element binary vector, as explained in the previous paragraph.

In the bottom left figure 4.13, we can see the evolution of the average distance between individuals as a function of the generation number. We see that this average distance decreases with the generations. Again, this is a typical value of GA, and this behaviour is a consequence of the behaviour of the mean FV evolution.

Finally, the bottom right figure 4.13 shows the FV of all the individuals of the current generation. As we are in the last generation, we see that most of the genes have a FV equal to 2. This plot for the first generation would show that most of our genes have high FV, but as our GA evolves, more and more genes becomes better fitted, as explained before.

4.4 Results

4.4.1 Different Classification Problems Studied

From now on we are going to call classes to the different groups of subjects we have. As a remainder we have 2 main classes: First Psychotic Episode (FPE) group and Control (CON group). From the FPE class we have made 3 different subclasses: schizophrenic pre (SZ pre), schizophrenic post (SZ post) and non-schizophrenic pre (nSZ pre). In order to deal with those different classes we have generated several classification problems, each one of them with two classes, as describe in the following list:

- CON vs FPE: In this classification problem we want to study the differences between CON subjects and subjects having an FPE, whether they are later diagnosed as SZ or not. In other words, we are studying the EEG changes between CON subjects and subjects suffering a FPE and before taking any medication. In order to have compensated classes for the classification problem (i.e. the same number of subjects for each class), we use 15 CON and 15 subjects suffering a FPE, from which 9 are SZ pre and 6 are nSZ pre. It is always a good practice to have compensated classes in classification problems in order not to overtrain a class while leaving the other one with a poor training.
- SZ pre vs nSZ pre: In this case we want to study the differences between subjects suffering a FPE episode and that in a later stage are diagnosed as SZ and subjects also suffering a FPE but that are not diagnosed as SZ. We call this problem differential diagnostic. Again in order to have compensated classes, we use 6 SZ pre and 6 nSZ pre.
- CON vs SZ pre: In this study, we want to study the differences between CON and SZ pre. We use 9 CON and 9 SZ pre.
- CON vs SZ post: This one is the similar to the previous study, but in this case we compare CON and SZ post. We use 7 CON an 7 SZ post.
- SZ pre vs SZ post: In this case, we study the differences between SZ pre and SZ post. This is a longitudinal study, in which we want to study the effects of the medication in the EEG. We use 7 SZ pre and 7 SZ post.
- CON vs SZ: In this final study, we compare CON subjects against SZ subjects whether they took medication or not. We use 16 CON and 16 subjects suffering SZ, from which 9 are SZ pre and 7 are SZ post.

In every case we have used balanced classes as stated before. This is a good practice in order not to overtrain one class with respect to the other. Moreover, as we are using a GA in order to select the features that optimise the performance of the classifier, if we have two non-balanced classes, we might end up having a system that is able to classify very well the overtrained class while leaving the other with a very poor performance. In other words, if we have 20 subjects in class A and 5 subjects in class B, our GA is maximising the number of correctly classified subjects from class A + the number of correctly classified subjects from class B, and thus the maximum is 25. We might have a performance of 20 over 25, which is very good, but it might happen that the 20 subjects from class A are correctly classified while none from class B are correctly classified. Such a classifier would be useless for a diagnostic purpose tool.

4.4.2 Method 1: Applying the GA for feature selection to all our data set

In order to compute the performance of the system, we have performed a cross-fold-validation using the leave-one-subject-out technique. That is, we have used all subjects from class A but 1 for training and all subjects from class B but 1 for training. The subjects from class A and class B not used for training are used for testing. Once we have computed the performance of the classifier for these 2 subjects, we choose another subject from class A and class B for testing and add the precedent ones in the training set. This is done for all the subjects. This is a commonly used technique that allows us to take as much profit of our available data: all subjects are used in the test set for the evaluation performance of the system, while we are keeping the training set as big as possible. We call this method 1.

Table 4.2 summarises the results we have achieved for two of our classification problems. Those two problems are very interesting for two reasons. First of all because we are using two classes with a high number of individuals (30 and 32 respectively) and thus the results are more significant from a statistical point of view. On the other hand because we are comparing the EEG features of CON vs FPE in one case and CON vs SZ in the other. In the first problem, we are studying the differences between a CON group with a group of patients suffering a FPE episode, before taking any medication, and before being diagnosed as SZ or not. Actually, as we can see in table 4.2, from our FPE group, we have 9 patients diagnosed as SZ at a later stage, and 6 that were not diagnosed as SZ. In the other problem in table 4.2, we are comparing CON vs SZ, no matter if they are taking medication or not (we mix in the same class SZ pre and SZ post).

Feature	CON vs FPE	CON vs SZ
CC	CON=13/15 (86.7%) SZ pre+nSZ pre=11/15 (73.3%)	CON=12/16 (75%) SZ pre+SZ post=9/16 (56.2%)
	from which SZ pre=6/9 (66.7%) nSZ pre=5/6 (83.3%)	from which SZ pre=6/9 (66.7%) SZ post=3/7 (42.9%)
	Overall=24/30 (80%)	**Overall=21/32 (65.6%)**
PL	CON=13/15 (86.7%) SZ pre+nSZ pre=11/15 (73.3%)	CON=10/16 (62.5%) SZ pre+SZ post=14/16 (87.5%)
	from which SZ pre=6/9 (66.7%) nSZ pre=5/6 (83.3%)	from which SZ pre=8/9 (88.9%) SZ post=6/7 (85.7%)
	Overall=24/30 (80%)	**Overall=24/32 (75%)**

Table 4.2: Performance of the classification problems CON vs FPE and CON vs SZ for both CC and PL (Method 1)

In the case of CON vs FPE, we reach a performance of 80% for both CC and PL features. The optimum DF and FB selected by the GA in the case of CC was Diagonal Quadratic and 30-45 Hz (low Gamma band) respectively. For PL, the GA chose Quadratic and 13-30 Hz (Beta band). In the second problem, CON vs SZ, we reach a slightly lower performance of 75% in the case of PL. In that case the GA chose the DF Diagonal Linear and FB 4-8Hz (Theta).

Feature	SZ pre vs nSZ pre	CON vs SZ pre
CC	SZ pre=4/6 (66.7%) nSZ pre=6/6 (100%)	CON=7/9 (77.8%) SZ pre=8/9 (88.9%)
	Overall=10/12 (83.3%)	**Overall=15/18 (83.3%)**
PL	SZ pre=4/6 (66.7%) nSZ pre=5/6 (83.3%)	CON=9/9 (100%) SZ pre=6/9 (66.7%)
	Overall=9/12 (75%)	**Overall=15/18 (83.3%)**
Feature	CON vs SZ post	SZ pre vs SZ post
CC	CON=6/7 (85.7%) SZ post=6/7 (85.7%)	SZ pre=5/7 (71.4%) SZ post=6/7 (85.7%)
	Overall=12/14 (85.7%)	**Overall=11/14 (78.6%)**
PL	CON=5/7 (71.4%) SZ post=6/7 (85.7%)	SZ pre=5/7 (71.4%) SZ post=6/7 (85.7%)
	Overall=11/14 (78.6%)	**Overall= 11/14 (78.6%)**

Table 4.3: Performance of the classification problems SZ pre vs nSZ pre, CON vs SZ pre, CON vs SZ post and SZ pre vs SZ post for both CC and PL (Method 1)

Table 4.3 shows the results of 5 extra classification problems we have implemented. The first one SZ pre vs nSZ pre has been implemented in order to see if our classifiers are able to distinguish between SZ pre and nSZ pre patients. This is a very interesting test since it allows us to do a differential diagnosis, i.e. can we distinguish among subjects having a FPE episode if they will be diagnosed as SZ on a later stage? As we can see we reach a performance of 83.3% in the case of CC feature (with DF = Linear and FB = 30-45 Hz which correspond to low Gamma). We then performed 3 other classification problems to distinguish between 3 classes: CON, SZ pre and SZ post. Regarding CON vs SZ pre we reached a performance of 83.3% for both CC (DF = Quadratic and FB = 45-90 Hz corresponding to high Gamma) and PL (DF = Linear and FB = 13-30 Hz corresponding to Beta). Regarding CON vs SZ post we reached a performance of 85.7% for CC (DF = Linear and FB = 30-45 Hz corresponding to low Gamma). Finally for SZ pre vs SZ post we reached a performance of 78.6% for both CC (DF = Diagonal Linear and FB = 30-45 Hz corresponding to low Gamma) and PL (DF = Diagonal Linear and FB = 30-45 Hz corresponding to low Gamma).

The results presented in Tables 4.2 and 4.3 are quite encouraging and show that in our data set there is a remarkable discrimination level between the different classes. In any case, as the GA is applied using all the available data, we are maximising the classification performance for our particular data set, and thus the generalisation power of the system might be compromised. In other words, we are tuning the features (using the GA) in order to reach the highest classification rate for our data, but this does not mean that with new data, the same performance would be expected.

4.4.3 Method 2: Performing the leave-one-subject-out before the GA

In order to study the generalisation power of our system we have performed other tests, in which we have applied the leave-one-out technique before the feature selection achieved by

the GA (method 2). By doing so, we can be sure that our system would have a very good generalisation power, even though a drop in the performance is also expected. What we do now is similar to what we describe before, but in this case the data of the subject we keep for testing does not participate in the feature selection performed by the GA. The feature selection is now performed using the rest of the subjects (i.e. the training subjects), and the best features found for this training group are now used for our test subject. By using this approach, the generalisation power of our system should not be compromised. The test subject does not participate in the feature selection process (the system has never 'seen' this data before) and thus any new incoming data should behave in a similar way. We have to take into account that we have a limited number of subjects, and that is why we performed the initial analysis using all the available data, but keeping in mind that this test should also be done. The results of this approach are presented in Tables 4.4 and 4.5.

Feature	CON vs FPE	CON vs SZ
CC	CON=11/15 (73.3%) SZ pre+nSZ pre=10/15 (66.7%)	CON=7/16 (43.7%) SZ pre+SZ post=9/16 (56.2%)
	from which SZ pre=6/9 (66.7%) nSZ pre=4/6 (66.7%)	from which SZ pre=6/9 (66.7%) SZ post=3/7 (42.8%)
	Overall=21/30 (70%)	**Overall=16/32 (50%)**
PL	CON=11/15 (73.3%) SZ pre+nSZ pre=10/15 (66.6%)	CON=6/16 (37.5%) SZ pre+SZ post=8/16 (50%)
	from which SZ pre=5/9 (55.5%) nSZ pre=5/6 (83.3%)	from which SZ pre=5/9 (55.5%) SZ post=3/7 (42.8%)
	Overall=21/30 (70%)	**Overall=14/32 (43.7%)**

Table 4.4: Performance of the classification problems CON vs FPE and CON vs SZ for both CC and PL performing the leave-one-subject-out before the GA (Method 2)

Feature	SZ pre vs nSZ pre	CON vs SZ pre
CC	SZ pre=5/6 (83.3%) nSZ pre=2/6 (33.3%)	CON=7/9 (77.8%) SZ pre=6/9 (66.7%)
	Overall=7/12 (58.3%)	**Overall=13/18 (72.2%)**
PL	SZ pre=3/6 (50%) nSZ pre=2/6 (33.3%)	CON=4/9 (44.4%) SZ pre=6/9 (66.7%)
	Overall=9/12 (41.7%)	**Overall=10/18 (55.6%)**
Feature	CON vs SZ post	SZ pre vs SZ post
CC	CON=5/7 (71.4%) SZ post=6/7 (85.7%)	SZ pre=5/7 (71.4%) SZ post=4/7 (57.1%)
	Overall=11/14 (78.6%)	**Overall=9/14 (64.3%)**
PL	CON=6/7 (85.7%) SZ post=3/7 (42.8%)	SZ pre=3/7 (42.8%) SZ post=5/7 (71.4%)
	Overall=9/14 (64.3%)	**Overall= 8/14 (57.1%)**

Table 4.5: Performance of the classification problems SZ pre vs nSZ pre, CON vs SZ pre, CON vs SZ post and SZ pre vs SZ post for both CC and PL performing the leave-one-out before the GA (Method 2)

As expected we see a performance drop, but in any case we see that we can still discriminate among classes in most of our classification problems. The first observation we can do is that in all the different classification problems, we observe that the CC feature provides better results than PL, except in the case SZ pre vs nSZ pre in which both features reach the same performance equal to 70%. In the case of CON vs SZ, we reach a performance of 50%, which corresponds to a random classification. This is the only case in which no discriminative power is found by our system. With the problems SZ pre vs nSZ pre and SZ pre vs SZ post we reach 58.3% and 64.3% respectively. The results are not impressive for these cases but some discriminative power is still found. Finally for CON vs SZ pre and CON vs SZ post we reach 72.2% and 78.6%. The results for these classification problems are more promising.

4.4.4 Method 3a: No feature selection applied using SL

In this section we have applied another approach (method 3a) without using any feature selection step. In other words, we have input all the feature vectors (from component 5 to 40) in the classifier, and the performances, as in the precedent tests, have been computed by using the leave-one-out technique. It is important to note that in this case the generalisation power is not compromised either, since we are not tuning the system with our data. Any new incoming data should behave in a similar way, i.e. should have a similar performance. We have worked with the same classification problems as before and we have done so for each one of the DFs and each one of the FBs, as shown in Table 4.6.

Discriminant Function		Linear						Diagonal Linear					
Classif. Problem	Feat.	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2
CON vs FPE	CC	53.3	50	46.7	63.3	73.3	**80**	50	56.7	56.7	43.3	76.7	76.7
CON vs FPE	PL	53.3	66.7	63.3	66.7	**70**	66.7	56.7	60	63.3	53.3	66.7	66.7
CON vs SZ	CC	53.1	46.9	37.5	46.9	50	**75**	62.5	50	46.9	31.3	53.1	56.3
CON vs SZ	PL	53.1	43.8	46.9	**65.6**	53.1	**65.6**	62.5	56.3	53.1	50	50	56.3
SZ pre vs nSZ pre	CC	41.7	41.7	50	33.3	75	66.7	33.3	58.3	58.3	25	50	50
SZ pre vs nSZ pre	PL	50	50	50	25	66.7	**75**	50	66.7	41.7	25	**75**	66.7
CON vs SZ pre	CC	33.3	50	50	72.2	66.7	72.2	61.1	50	55.6	33.3	72.2	**77.8**
CON vs SZ pre	PL	44.4	55.6	61.1	**66.7**	55.6	55.6	61.1	50	55.6	44.4	55.6	55.6
CON vs SZ post	CC	42.9	35.7	57.1	50	64.3	**78.6**	50	64.3	71.4	35.7	64.3	57.1
CON vs SZ post	PL	35.7	42.9	50	**71.4**	57.1	**71.4**	50	64.3	50	21.4	50	50
SZ pre vs SZ post	CC	50	50	50	35.7	57.1	64.3	42.9	57.1	42.9	35.7	64.3	**71.4**
SZ pre vs SZ post	PL	57.1	57.1	42.9	50	64.3	**71.4**	21.4	50	42.9	42.9	64.3	64.3
Discriminant Function		Quadratic						Diagonal Quadratic					
Classif. Problem	Feat.	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2
CON vs FPE	CC	46.7	50	40	53.3	70	76.7	50	43.3	46.7	33.3	76.7	73.3
CON vs FPE	PL	60	66.7	63.3	**70**	56.7	63.3	53.3	53.3	60	50	**70**	63.3
CON vs SZ	CC	56.3	43.8	46.9	31.3	46.9	65.6	59.4	43.8	50	37.5	53.1	59.4
CON vs SZ	PL	50	53.1	59.4	62.5	46.9	62.5	53.1	56.3	56.3	46.9	53.1	56.3
SZ pre vs nSZ pre	CC	16.7	50	58.3	50	75	**91.7**	25	50	66.7	33.3	33.3	58.3
SZ pre vs nSZ pre	PL	41.7	33.3	33.3	41.7	58.3	66.7	41.7	66.7	41.7	33.3	58.3	58.3
CON vs SZ pre	CC	55.6	50	55.6	50	72.2	61.1	61.1	38.9	44.4	38.9	66.7	**77.8**
CON vs SZ pre	PL	33.3	50	50	61.1	44.4	61.1	50	55.6	50	50	55.6	50
CON vs SZ post	CC	57.1	64.3	57.1	35.7	57.1	71.4	64.3	64.3	50	28.6	57.1	50
CON vs SZ post	PL	50	35.7	64.3	50	42.9	50	57.1	57.1	57.1	42.9	42.9	57.1
SZ pre vs SZ post	CC	50	50	57.1	35.7	64.3	50	35.7	50	35.7	21.4	64.3	57.1
SZ pre vs SZ post	PL	42.9	57.1	57.1	57.1	57.1	50	35.7	50	42.9	42.9	57.1	57.1

Table 4.6: Performance in percentages of our different classification problems for both CC and PL (using SL as Synchronicity Feature) without applying feature selection (Method 3). In bold we can see the higher performance for each problem. As it can be seen in the table, we have tested 4 different DFs: Linear, Diagonal Linear, Quadratic and Diagonal Quadratic

4.4.5 Method 3b: No feature selection applied using CO

As a final test, we have also applied the same complex network approach, by using the Coherence (CO) feature rather than SL, just for comparison purposes. As explained in section 4.3, CO has been widely used in the analysis of the EEG signals to study the 'disconnection hypothesis', but this feature is not sensitive to non-linear dynamical interdependencies. In the table we can see the results using all the feature vectors (i.e. we are not applying a feature selection, just as in previous method 3a) for each classification problem, FB and DF.

Discriminant Function		Linear						Diagonal Linear					
Classif. Problem	Feat.	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2
CON vs FPE	CC	60.0	60.0	56.7	16.7	60.0	63.3	56.7	66.7	63.3	36.7	**73.3**	70.0
CON vs FPE	PL	53.3	63.3	43.3	46.7	63.3	63.3	56.7	**66.7**	63.3	36.7	63.3	63.3
CON vs SZ	CC	62.5	65.6	62.5	53.1	65.6	56.3	59.4	**68.8**	**68.8**	62.5	71.9	65.6
CON vs SZ	PL	59.4	**68.8**	65.6	53.1	**68.8**	65.6	59.4	**68.8**	**68.8**	65.6	65.6	56.3
SZ pre vs nSZ pre	CC	25.0	58.3	66.7	33.3	83.3	**100.0**	41.7	16.7	33.3	41.7	41.7	75.0
SZ pre vs nSZ pre	PL	41.7	50.0	58.3	25.0	**100.0**	**100.0**	41.7	58.3	58.3	50.0	58.3	50.0
CON vs SZ pre	CC	55.6	44.4	16.7	38.9	61.1	61.1	38.9	55.6	44.4	38.9	**83.3**	77.8
CON vs SZ pre	PL	50.0	50.0	27.8	44.4	66.7	66.7	38.9	55.6	38.9	50.0	**72.2**	66.7
CON vs SZ post	CC	57.1	57.1	35.7	28.6	57.1	50.0	50.0	57.1	35.7	35.7	57.1	50.0
CON vs SZ post	PL	42.9	50.0	28.6	35.7	42.9	50.0	50.0	50.0	42.9	28.6	50.0	35.7
SZ pre vs SZ post	CC	35.7	21.4	28.6	35.7	35.7	42.9	14.3	21.4	21.4	35.7	50.0	57.1
SZ pre vs SZ post	PL	28.6	28.6	35.7	50.0	28.6	42.9	21.4	28.6	21.4	42.9	42.9	**64.3**
Discriminant Function		Quadratic						Diagonal Quadratic					
Classif. Problem	Feat.	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2	Theta	Alpha1	Alpha2	Beta	Gamma1	Gamma2
CON vs FPE	CC	56.7	50.0	46.7	46.7	60.0	66.7	53.3	63.3	60.0	46.7	66.7	70.0
CON vs FPE	PL	46.7	46.7	43.3	33.3	60.0	60.0	53.3	63.3	60.0	43.3	60.0	56.7
CON vs SZ	CC	53.1	62.5	56.3	50.0	56.3	62.5	56.3	62.5	62.5	46.9	62.5	59.4
CON vs SZ	PL	53.1	53.1	53.1	50.0	**68.8**	**68.8**	**68.8**	62.5	65.6	46.9	53.1	53.1
SZ pre vs nSZ pre	CC	25.0	25.0	33.3	25.0	83.3	75.0	33.3	25.0	50.0	33.3	41.7	50.0
SZ pre vs nSZ pre	PL	50.0	41.7	41.7	33.3	58.3	58.3	50.0	58.3	58.3	58.3	58.3	58.3
CON vs SZ pre	CC	44.4	50.0	44.4	61.1	55.6	66.7	38.9	55.6	50.0	44.4	61.1	77.8
CON vs SZ pre	PL	38.9	44.4	38.9	38.9	61.1	66.7	44.4	50.0	44.4	44.4	66.7	66.7
CON vs SZ post	CC	50.0	50.0	50.0	57.1	50.0	57.1	50.0	50.0	42.9	42.9	**71.4**	50.0
CON vs SZ post	PL	42.9	42.9	42.9	50.0	64.3	**71.4**	57.1	57.1	28.6	14.3	57.1	35.7
SZ pre vs SZ post	CC	57.1	50.0	57.1	**64.3**	42.9	57.1	28.6	35.7	35.7	35.7	35.7	42.9
SZ pre vs SZ post	PL	57.1	57.1	50.0	**64.3**	42.9	42.9	28.6	28.6	35.7	35.7	35.7	50.0

Table 4.7: Performance in percentages of our different classification problems for both CC and PL (using CO as Synchronicity Feature) without applying feature selection (Method 3). In bold we can see the higher performance for each problem. As it can be seen in the table, we have tested 4 different DFs: Linear, Diagonal Linear, Quadratic and Diagonal Quadratic

We can see that in general the performance is higher for the SL feature, proving that this feature is best suited for our analysis, likely due to the fact that SL is sensitive to existing non-linear dependencies of the EEG signals. These results agree with (Breakspear et al. [97]). In any case, we have a very interesting result concerning the classification problem SZ pre vs nSZ pre: we reach a perfect classification (i.e. lower than 100%) for the linear DF and for the Gamma2 FB for both PL and CC. For this specific problem, it seems that CO yields better results that SL. This is an important fact to take into account.

4.4.6 Summary

In Table H.5 we summarise the best results for each one of the methods applied in the performance evaluation for each one of the classification problems.

	method 1				method 2		method 3 with SL				method 4 with CO			
Classif. Problem	Perf.	Feat.	DF	FB	Perf.	Feat.	Perf.	Feat	DF	FB	Perf.	Feat	DF	FB
CON vs FPE	80	CC	D. Quad.	Gamma1	70	CC	76.7	CC	D. Lin	Gamma1	73.3	CC	D. Lin	Gamma1
CON vs SZ	75	PL	D. Lin.	Theta	50	CC	65.6	PL	Lin.	Beta	68.8	CC	Lin.	Gamma1
SZ pre vs nSZ pre	83.3	CC	Lin.	Gamma1	58.3	CC	75	CC	Lin.	Gamma1	100	CC	Lin.	Gamma2
CON vs SZ pre	83.3	CC	Quad.	Gamma2	72.2	CC	72.2	CC	Lin.	Gamma2	83.3	CC	D. Lin.	Gamma1
CON vs SZ post	85.7	CC	Lin	Gamma1	78.6	CC	78.6	CC	Lin.	Gamma2	71.4	PL	Quad.	Gamma2
SZ pre vs SZ post	78.6	CC	D. Lin.	Gamma1	64.3	CC	64.3	CC	D.Lin.	Gamma1	64.3	CC	Quad.	Beta

Table 4.8: Summary of the best performances reached by each one of the methods of our different classification problems. For method 2, DF and FB are computed for each subject, and thus are not provided. Note that we are selecting the FB and DF that provides the best performance for each case

As a summary for this section, we have generated Figure H.1 that shows the performance behaviour for each method applied and for each classification problem. It is important to note that in this case we have selected a given Complex Graph feature, FB and DF for method 3 with SL (CC, Gamma2 and Linear, respectively) and for method 3 with CO (PL, Gamma2 and Linear). This is somehow more fair than selecting each time the combination of Complex Network feature, FB and DF that provides the best performance for each classification problem. This figure is very interesting since we can easily see the performance of each one of the methods , and thus compare between them, with a quick look.

As expected, method 1 outperforms the other methods (except for the case of SZ pre vs nSZ pre). This is expected, as we commented in its corresponding section: as we are applying a GA to the whole data set, we are tuning our system to provide the highest possible performance. The problem with this method is that in principle, the generalisation power cannot be guaranteed.

Method 2 provides a lower performance, but at least the methodology applied guarantees the generalisation capacities of the system (as a remainder the GA algorithm was applied after applying the leave-one-out technique, and thus the system did not 'see' the testing data before applying the classification).

Method 3a using SL feature provided good results and in this case as no feature selection was performed (we use all the threshold extracted from the graphs), the generalisation capacities should also be guaranteed in this case.

Finally, and just for comparison purposes, we applied method 3b but now using CO as synchronicity feature. The performance is lower than method 3a with SL except for the case of SZ pre and nSZ pre, in which we reach a perfect performance (100%). For this particular classification problem, it might be better to use CO rather than SL, but in the other classification problems SL behave better and thus seems as a more robust feature for our purposes.

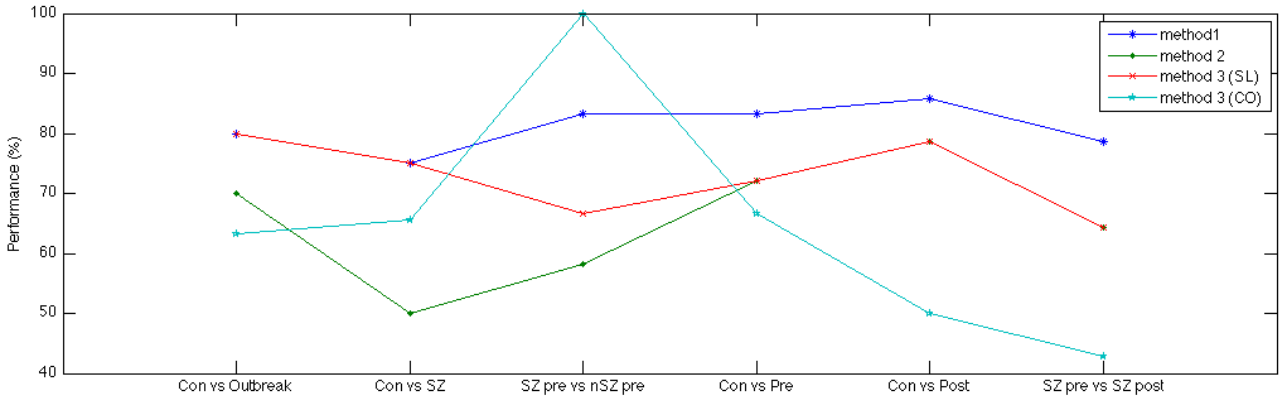

Figure 4.14: Performance for each classification problem and for each method applied

4.5 Conclusion and Discussion

In this research an EEG data set recorded to a number of SZ patients has been analysed. Actually, this data set is divided in several subgroups: SZ pre, SZ post and nSZ pre. Along

with the recording of the patients we have also the same EEG data set recorded to a group of healthy control (CON) subjects.

We have performed an original data analysis in which we have applied advanced signal processing techniques combined with Computational Intelligence (CI) techniques. We have extracted the Synchronisation Likelihood (SL) feature from each pair of channels (and also the Coherence (CO) for comparison purposes) and created a graph for each one of the EEG epochs. Doing so we were able to compute the Path Length (PL), the Clustering Coefficient (CC) and the Connectivity Index (KI) of each graph as a function of a threshold applied to the SL (or CO) of each pair of channels. These two vectors (PL and CC) are the features we have used in the classification stage. The KI was discarded from the analysis since it showed lower discriminative power among classes compared to PL and CC.

As we had a high number of features (we have worked with 6 different frequency bands of the original EEG signals), we have implemented a feature selection stage based on a Genetic Algorithm (GA). By doing so, we have been able to reach quite significant performances in the classification stage. As explained in the Results section 4.4, we have applied the GA in 2 different approaches. In method 1 we have used all our data to select the most suited features for each classification problem. By doing so, we reach the higher performances, but this methodology has a drawback: we are tuning our system in order to maximise the performance for our particular data. This means that if we input new data in our system, the performance might not be as good as the one obtained with our own data. In other words, the generalisation capability is not guaranteed. That is why we applied another approach (method 2) in which we still use the same GA but now we leave out the data of a subject (test set), apply the GA to the rest of our data (training set) and with the selected features from our training set, we perform the classification to our test set. This is repeated for each one of the subjects, and because of that, the GA algorithm needs to be applied as many times as subjects we have. In each one of these iterations, different features are obtained for each subject. This method shows a performance degradation, but on the other hand, the generalisation performance has not been compromised. This is because the data of the test subject has not been used in the feature selection stage, and thus any new incoming data would be treated in exactly the same way. It is important to note that we have a limited amount of data, and that it is expected that having more data would allow us to better characterise the features and classifiers, and thus an increase of performance would be expected. Finally we have performed a last performance evaluation (method 3) in which we have not performed any feature selection stage: we have used the whole feature vectors (from component 5 to 40) for the classification stage. This approach provided quite remarkable results, better than method 2, but worse than method 1, as expected because we are not tuning the features for our data in this case. The results of method 3 are quite encouraging and moreover do not compromise the generalisation of the system for new incoming data. Note that method 3 was applied two times, one using SL as synchronicity feature and the other one using CO.

Several classification problems have been defined and performed with our data set. In the first place we have divided our data set in two classes: CON vs FPE. This study allows us to understand how discriminative is the EEG of the CON subjects versus a patient suffering a FPE, independently of the later diagnosis (i.e. whether the patient is later diagnosed as SZ or not). We have reached a performance of 80%, 70%, 80% and 63.3 % (for method 1, 2, 3(SL) and 3(CO) respectively), which demonstrate that there is a considerable difference between

both classes. Actually, these results are not surprising since it has been already reported in other studies that SZ EEG differs statistically from healthy EEG. There are two novelties in this particular study. On the one hand, we have applied a stage of Machine Learning (ML) to perform the classification, and we are working on a subject to subject basis. That means that there is a diagnostic potential in our system. On the other hand, we have also included a set of patients that were not diagnosed as SZ but came to the hospital with schizophrenic like symptoms.

We have also done a similar study by studying the differences of CON vs SZ. In this case we wanted to study the discriminative power between the CON class versus the SZ class, whether the SZ patient has taken medication or not. In this case we have reached a lower performance of 75%, 50%, 75% and 65.6% (for method 1, 2, 3a(SL) and 3b(CO) respectively) but significantly high compared for method 1 and 3 compared to a random classification (50%). No discriminative power is found for method 2.

From our point of view, the more interesting study is the one in which we have studied the differences between SZ pre and nSZ pre. In this case we are performing a differential diagnosis. Can we discriminate using only EEG if a subject suffering a FPE will be diagnosed as SZ on a later stage? In this case we have reached a quite high performance considering all the different studies presented here: 83.3%, 58.3%, 66.7% and 100% (for method 1, 2, 3a(SL) and 3b(CO) respectively). This application would be with no doubt very useful for psychiatrists, as an extra source of information, to determine what kind of treatment a patient suffering a FPE should follow.

Finally we have performed three different classification problems to compare between CON, SZ pre and SZ post. The performances we have reached are 83.3%, 72.2%, 72.2% and 66.7% for CON vs SZ pre, 85.7%, 78.6%, 78.6% and 50% for CON vs SZ post and 78.6%, 64.3%, 64.3% and 42.9% for SZ pre vs SZ post (again for method 1, 2, 3a(SL) and 3b(CO) respectively). These results are quite encouraging as well. It is surprising that the performance of the problem CON vs SZ post is higher than CON vs SZ pre. One might think that the EEG differences should be stronger in a SZ pre patient (while having a FPE) than in a SZ post patient (after taking medication) when compared to CON. Our explanation is that in this particular problem, the medication taken since the FPE, does affect the EEG signal, and in a deeper level the brain connectivity of the SZ patients. It would be very interesting to have access to a larger data set in order to do more studies and find deeper tendencies. It is also worth a comment to note that our system can also find strong differences between SZ pre and SZ post (up to 78.6% of performance for method 1). This is an interesting result that indicates that the medication taken by the patients is indeed affecting their EEGs.

An interesting conclusion of this study is that in general, we have seen that the best feature for the different classification problems is the CC feature (except for the case of CON vs SZ, which on the other hand is the classification problem that reached the lowest performance). We have also seen that the greater discriminative power is found in the Gamma Frequencies which agrees with the literature (see for example Uhlhaas and Singer [92] Sun et al. [91] Minzenberg et al. [90]).

In the recent years, there has been some discussion about the influence of EMG in the EEG recordings. Some works such as Kumar et al. [101] and McMenamin et al. [102] deals with this problem. They argue that EMG overlaps with all EEG frequencies of interest and

that a special attention should be taken when working specially in the high frequency bands. Remarkably, our best performances have been reached in the Gamma band and thus our results might be influenced by EMG artefacts. This should be investigated further. In any case, discriminative power has also been found in lower frequency bands that are not so much affected by EMG as shown in tables 4.7 and 4.6.

As a last word, we want to emphasise the potential use of the system described in this work. As it has been demonstrate, we are able to classify different problems comparing FPE patients in different conditions with CON subjects. Although we know the performance is not perfect (100%), we believe that such a tool would be useful to a psychiatrist that is responsible for the diagnosis of patients suffering from different mental diseases, and thus responsible of prescribing appropriate treatments. Just by performing a fast, cheap and non-invasive EEG, the psychiatrist would have access to an objective source of information (with well-established confidence levels) that could help him to better perform his/her diagnostics. We are also confident that our system could be used as well to perform diagnosis of different mental disorders, such as depression, Alzheimer's Disease (AD), Bipolar Disorder (BD), autism and so on. In any case, further studies should be made with different data sets covering those different conditions to determine that with confidence in order to extract further conclusions.

4.6 Complementary Figures

In the following figures, the errors bars represent the standard deviation of the mean.

4.6.1 CC, PL and KI for First Psychotic Episode group vs Control group

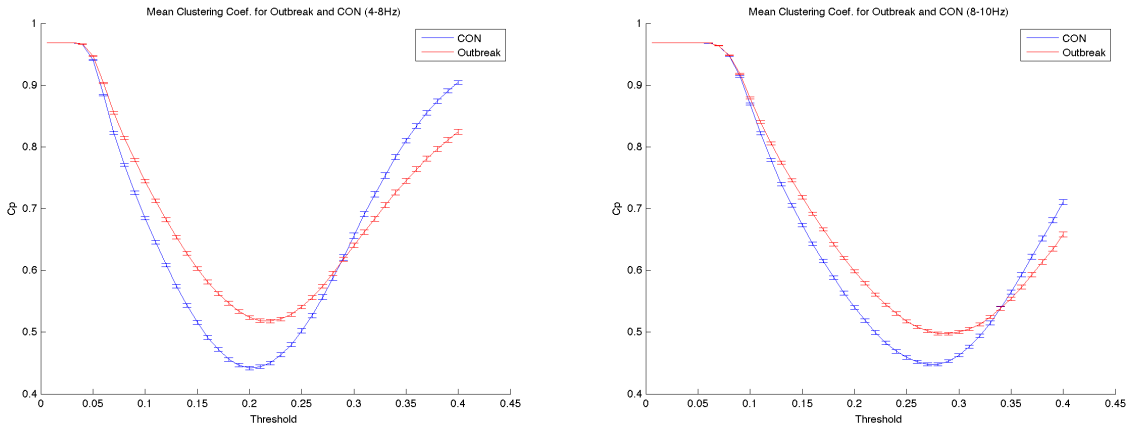

Figure 4.15: Mean over subjects of the Clustering Coefficient for FPE group and control group for FB 4-8Hz (left) and 8-10Hz (right)

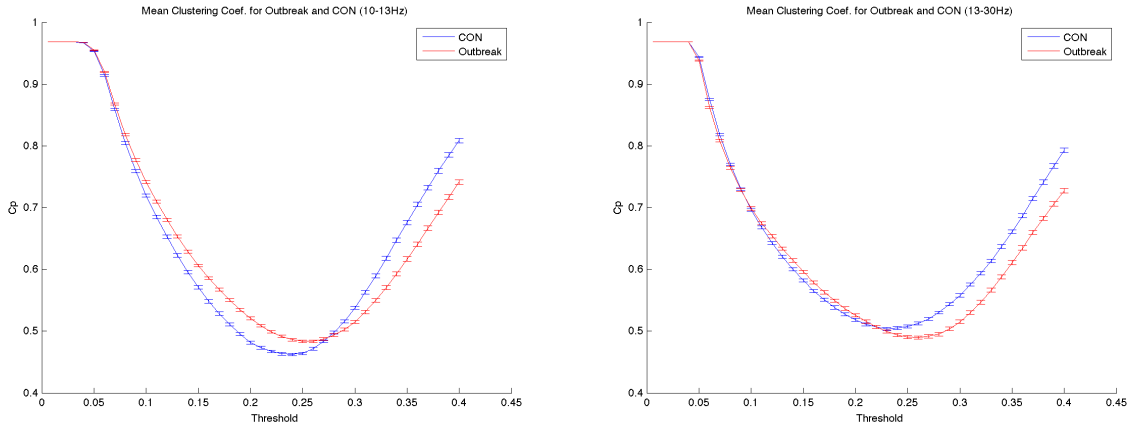

Figure 4.16: Mean over subjects of the Clustering Coefficient for FPE group and control group for FB 10-13Hz (left) and 13-30Hz (right)

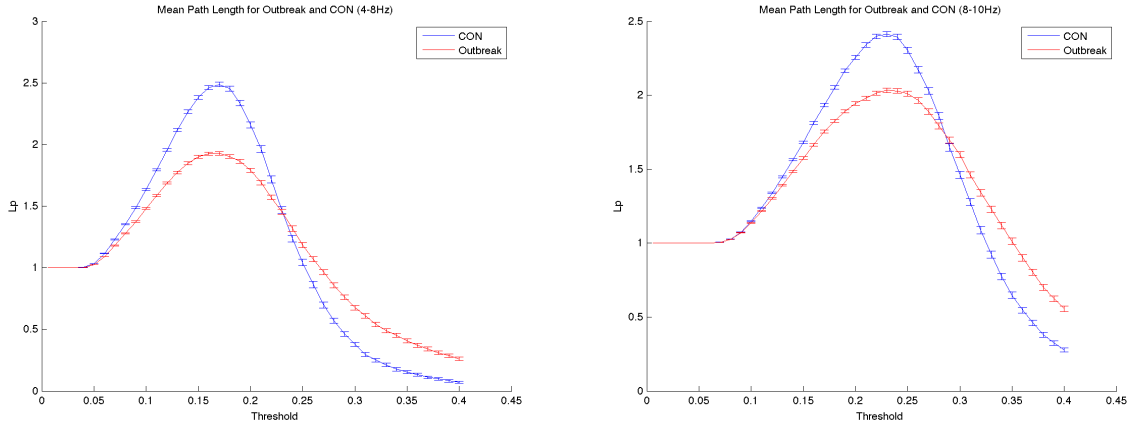

Figure 4.17: Mean over subjects of the Path Length for FPE group and control group for FB 4-8Hz (left) and 8-10Hz (right)

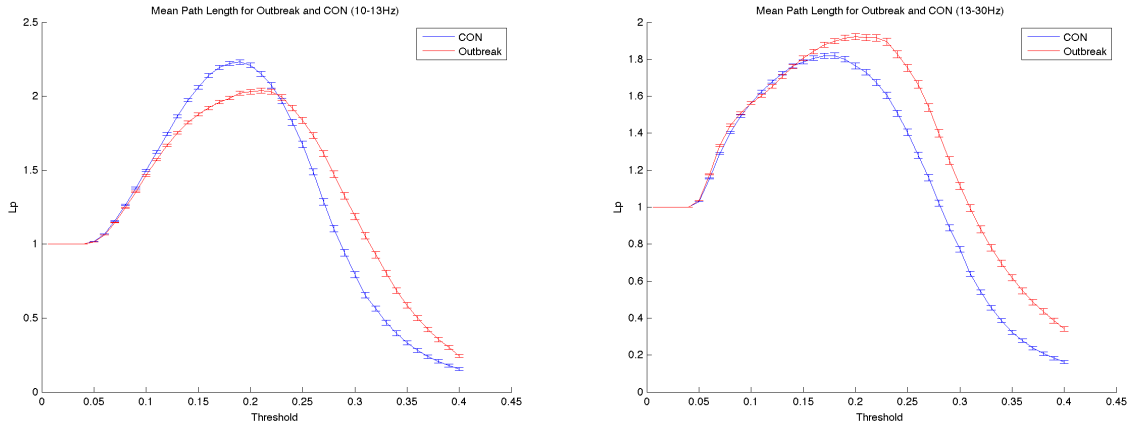

Figure 4.18: Mean over subjects of the Path Length for FPE group and control group for FB 10-13Hz (left) and 13-30Hz (right)

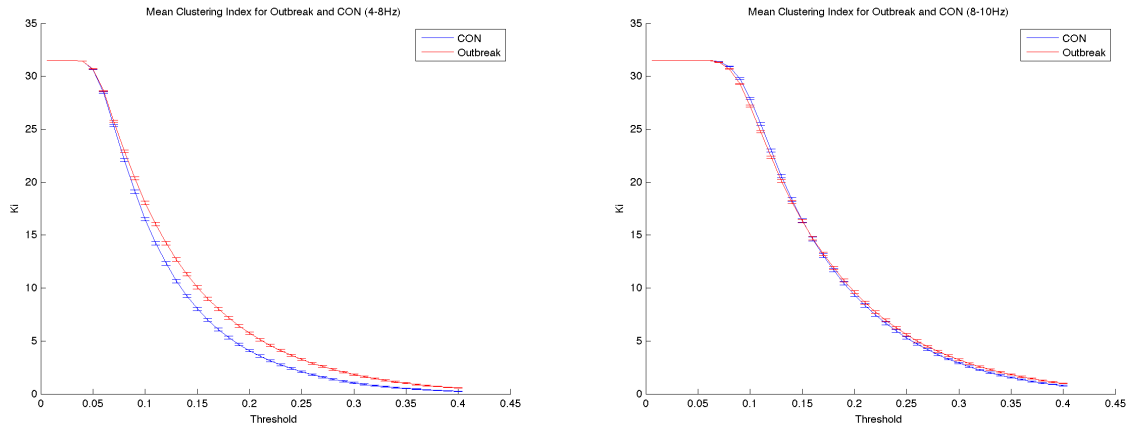

Figure 4.19: Mean over subjects of the Clustering Index for FPE group and control group for FB 4-8Hz (left) and 8-10Hz (right)

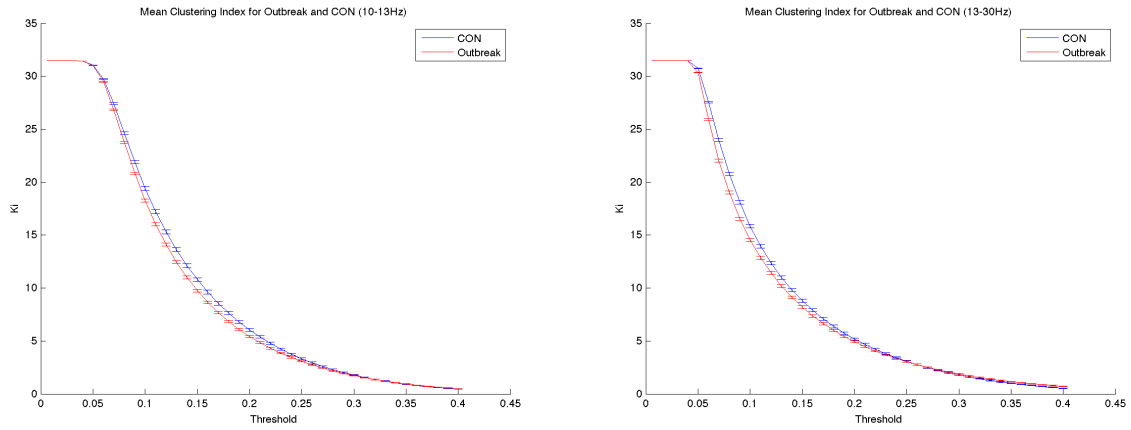

Figure 4.20: Mean over subjects of the Clustering Index for FPE group and control group for FB 10-13Hz (left) and 13-30Hz (right)

4.6.2 CC, PL and KI for each group (CON, SZ pre, SZ post and nSZ)

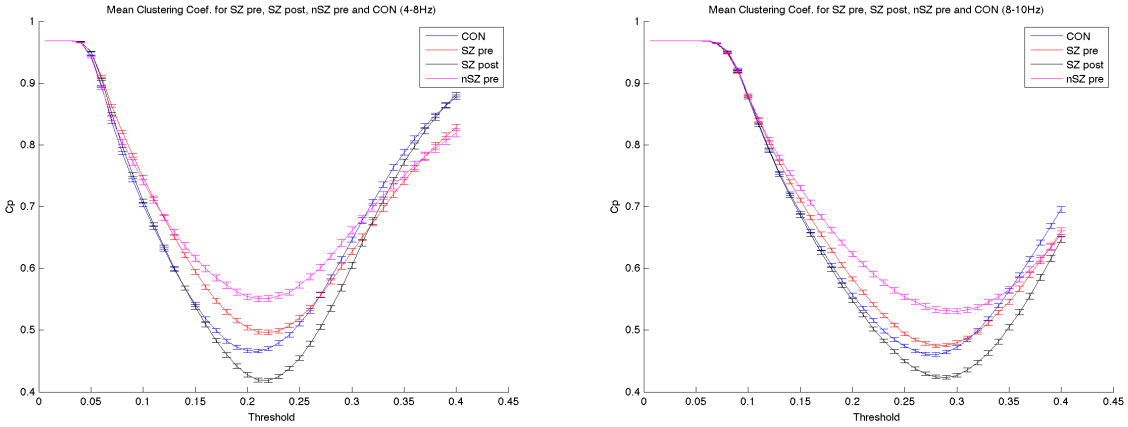

Figure 4.21: Mean over subjects of the Clustering Coefficient for each group for FB 4-8Hz (left) and 8-10Hz (right)

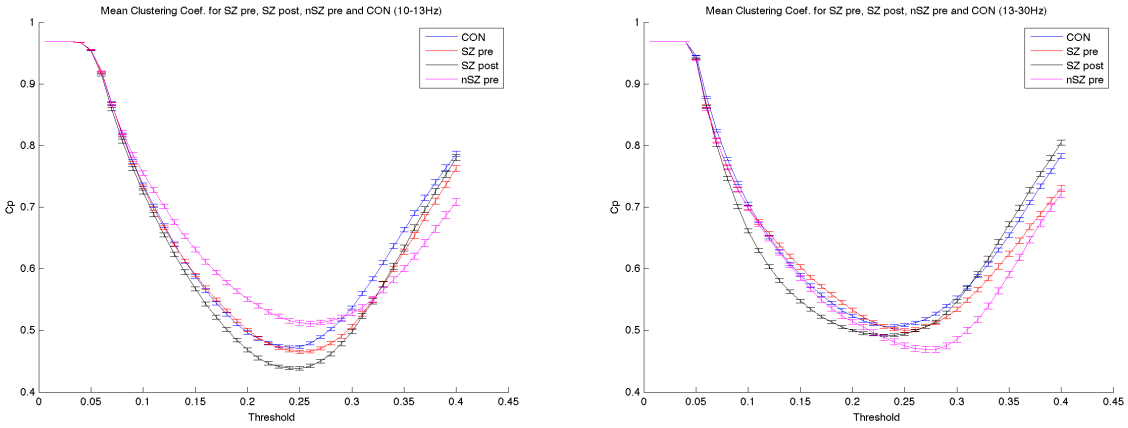

Figure 4.22: Mean over subjects of the Clustering Coefficient for each group for FB 10-13Hz (left) and 13-30Hz (right)

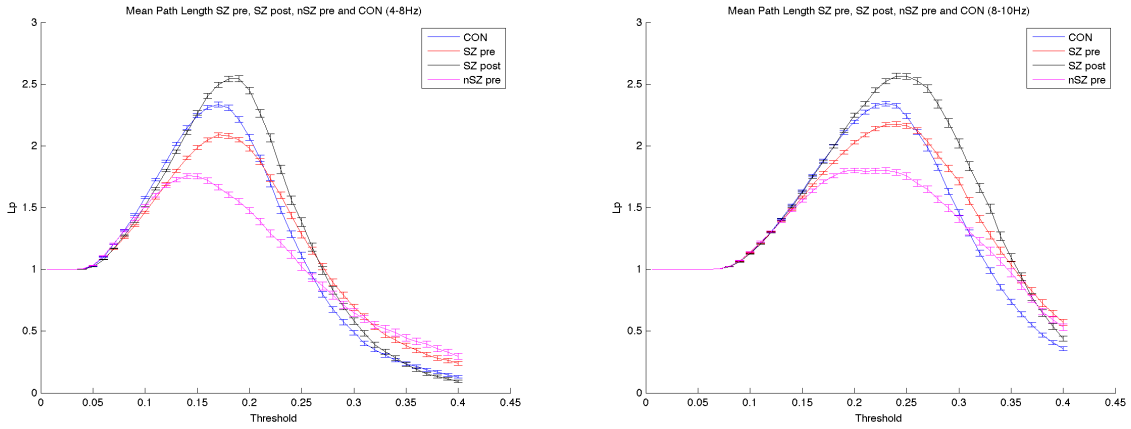

Figure 4.23: Mean over subjects of the Path Length for each group for FB 4-8Hz (left) and 8-10Hz (right)

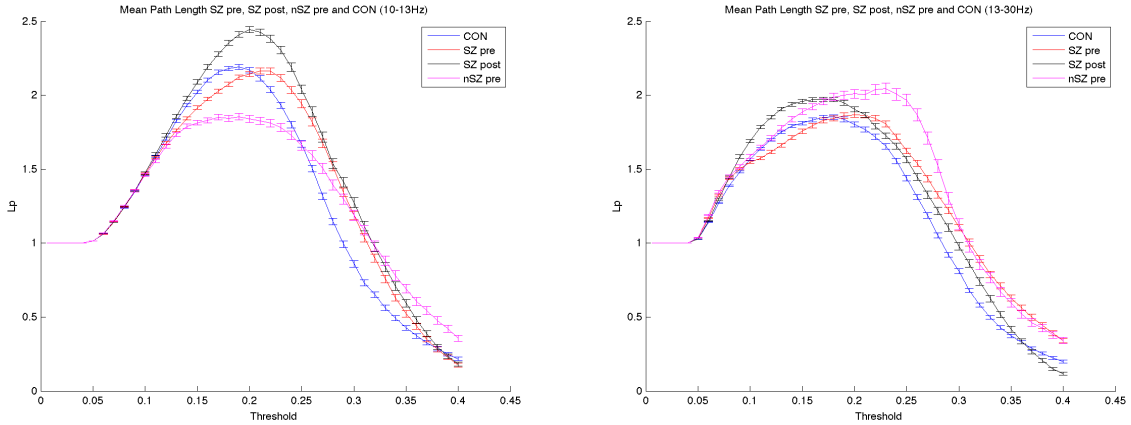

Figure 4.24: Mean over subjects of the Path Length for each group for FB 10-13Hz (left) and 13-30Hz (right)

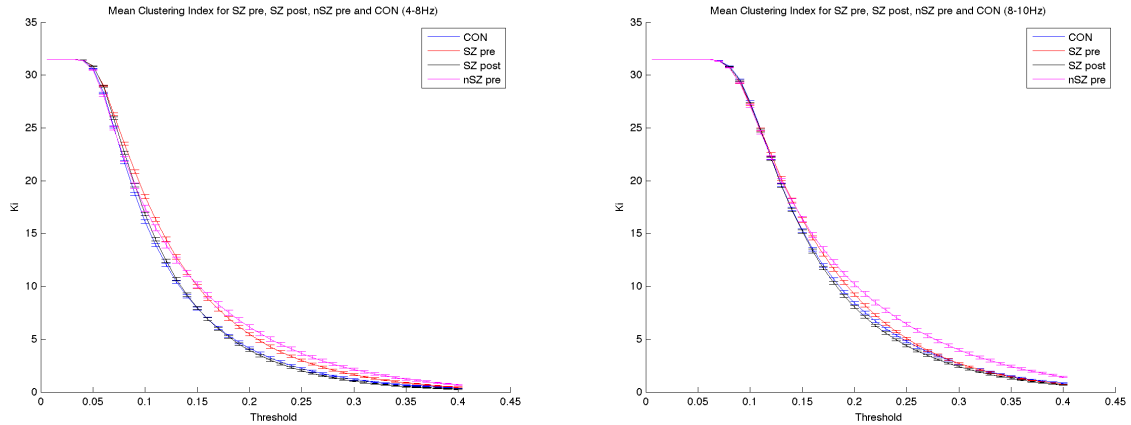

Figure 4.25: Mean over subjects of the Connectivity Index for each group for FB 4-8Hz (left) and 8-10Hz (right)

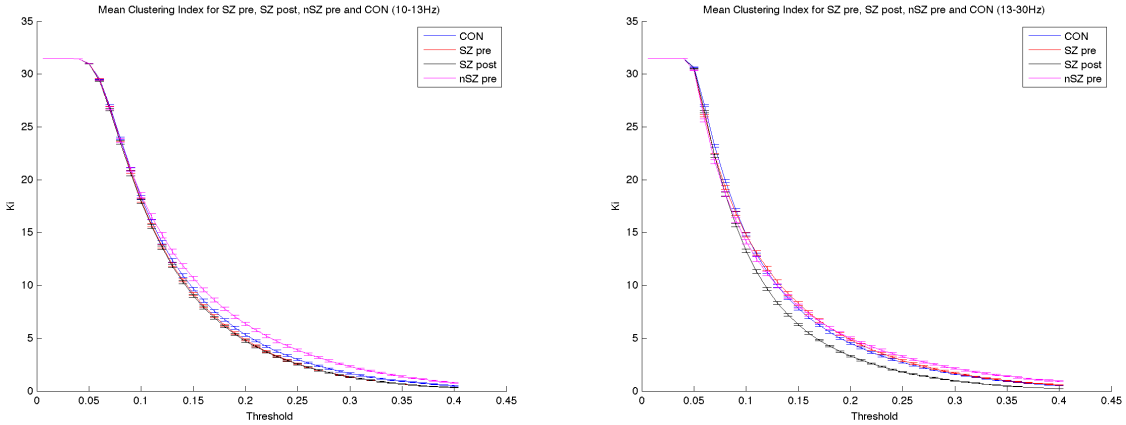

Figure 4.26: Mean over subjects of the Connectivity Index for each group for FB 10-13Hz (left) and 13-30Hz (right)

Chapter 5

Stress Markers in the EEG signals

In this last chapter we present our work related with stress markers in the EEG signal. We undertook an experiment in which we measured EEG to a set of participants while they performed a number of tasks specifically designed to elicit different stress levels. We were able to find statistical correlations between stress levels with a number of EEG features. We then applied Machine Learning (ML) techniques to classify the different stress levels with success, as explained in section 5.6.

5.1 Introduction

Stress is a very common condition in modern society. For example, it is estimated that stress costs British industry 3 billion British pounds per year (Kalia [103]). This is due mainly because people suffering from stress and related disorders experience impaired physical and mental functioning, more work days lost, increased impairment at work and a high use of health care services. Beside the economic impact of stress, there are also the negative consequences that individuals suffer. There are studies relating stress with physical diseases as well as with mental diseases (Cohen et al. [104]).

There are several types of stress such as psychological stress, chronic stress and Post-Traumatic Stress Disorder (PTSD). According to Cohen et al. [104], "Psychological Stress" occurs when an individual perceives that environmental demands tax or exceed his or her adaptive capacity. Chronic stress occurs when an individual is exposed to psychological stress for a prolonged period of time. In that case, the individual often feels he or she has no control. The endocrine system response will be the release of corticorteroids and finally long term negative effects on his/her mental and physical health will occur. Finally PTSD occurs when an individual suffers an intense trauma and again the mental and physical effects can be very negative as well. An example is an individual suffering a kidnapping or veteran soldiers after a war. In the case of our research we have focused on psychological stress, and we have mainly studied the EEG changes under different situations.

How EEG is affected by stress has been studied before in different works. In (Lewis et al. [53]), the effect of a naturalistic stressor on frontal EEG asymmetry, stress, and health has

been studied. The naturalistic stressor was a high examination period compared to a low examination period. The authors found interesting correlations between health and EEG frontal asymmetry (brain laterality). In their findings, they relate greater left frontal activity with low stress and increasing right frontal activity with high stress. There were also changes in the perceived stress level felt by the students, measured through standard questionnaires. No cortisol level changes were found between both periods.

In this other work (Kemp et al. [55]), the authors study the EEG Alpha Asymmetry in 3 populations: Major Depressive Disorder (MDD) patients, PTSD patients and healthy controls. Among their findings we have: reduced left-frontal activity in MDD, a positive correlation between PTSD severity and right-frontal lateralisation, greater activity in PTSD patients relative to MDD within the right-parietotemporal region and globally increased alpha power in MDD.

A last interesting work worth mentioning is the one presented in (Gaylord et al. [52]). The authors study the long term effects of three different stress treatment therapies on a group of Afro-American college students. These techniques included Transcendental Meditation (TM), Progressive Muscle Relaxation (PMR) and Cognitive-Behavioral strategies (CB).

Stress studies have been also conducted with Functional Magnetic Resonance Imaging (fMRI) and Positron Emission Tomography (PET) techniques. For instance in (Dedovic et al. [105]), they used a protocol called Montreal Imaging Stress Task (MIST), derived from the Trier Mental Challenge Test. Actually, the protocol we designed in our research has some common points with the protocol used in this work. The results reported by the authors include, on the one hand that levels of salivary free cortisol for the whole group were significantly increased under the experimental condition, relative to the control and rest conditions. On the other hand, performing mental arithmetic was linked to activation of motor and visual association cortices, as well as brain structures involved in the performance of these tasks (e.g., the angular gyrus).

In our research we have focused on EEG, although we also recorded other physiological signals and made the participants fill questionnaires to study their self-reported emotional levels. Based on the literature (for example Gotlib et al. [106], Lewis et al. [53] and Zhang and Lee [44]), we have mainly used Alpha Asymmetry and Beta/Alpha ratio features. We undertook a data recording campaign with 12 participants that had to perform a number of tasks designed to induce different levels of stress. Some actors were also present in the second part of the recording with the purpose of inducing social stress. The protocol description, the data analysis and the results are described in the next sections.

5.2 Objectives

The main scope of this research is to find stress markers in the EEG signal. A number of experiments took place at Starlab Barcelona S.L. premises. Besides EEG signals, facial EMG, EOG, ECG and Galvanic Skin Response (GSR) signals have also been recorded. We also made the volunteers fill a questionnaire to report their levels of several emotions. The main objective is to identify the most suited features related with stress in the EEG signals. In order

to do so we will analyse the peripheral sensor information and the results of the self-report questionnaires. These two independent sources of information will be used to study if we are really inducing different stress levels to the participants. We expect that the Relax task will induce less stress than the Fake Blood Sample task for instance (these tasks are described later in the text). But in order to be sure of that, we will analyse all the available information. Once we identify relevant tasks from a stress level point of view, we will see if are able to distinguish them by using only EEG features. In other words, we will use the peripheral sensor information and the self-report questionnaires as ground-truth for our EEG analysis.

This research was done within the INTERSTRESS European Project (see annex A for further information).

5.3 Participants

Twelve volunteers participated in the data collection (6 males and 7 females). The age of the participants went from 18 to 40 years (mean = 30.1 years, standard deviation = 7.9 years). Participants were informed about the main points of the INTERSTRESS project and about the experiments they took part. Just before the experiment, the participant and the researcher had to read and sign the document of consent.

There were also 3 actors present in the second part of the experiments, as explained below.

5.4 Materials and Methods

The definition of a protocol for such a recording campaign is a challenge by itself. Research on literature has been undertaken and two classical Psychophysiological protocols have been found. Those are the Trier Social Stress Test (TSST) and the Stroop Colour Word Interference task.

In few words, the TSST is a motivated performance task consisting of a brief preparation period (3 minutes) followed by a test period in which the subject has to deliver a free speech (5 minutes) and perform mental arithmetic (5 minutes) in front of an audience. More than 15 years ago, the TSST was introduced as a standardised protocol for the induction of moderate psychosocial stress in laboratory settings. In our case we have used three actors that performed as the audience, and we also used the mental arithmetic task. For more information on the original TSST please refer to Kirschbaum et al. [107] and Kudielka [108].

In the Stroop Colour Word Interference task, the subject has to read aloud the names of some colours, but the colours of the text are not the same with the names they read. This protocol has been applied since 1935 (Stroop [109]) and has been widely used in neuropsychological test. In our case, we selected this test because it seems a simple task but people have more trouble performing it than they expect, thus generating some frustration in the subjects. Moreover the subjects have to be quite concentrated while performing this task and that generates an engaged emotional state. A review on the use of the Stroop color-word test can be found in the work of (Jensen and Rohwer [110]).

The Biosemi ActiveTwo system has been selected to record the EEG. A configuration of 32 electrodes for EEG recording was used. The electrodes were attached to the head of the participant using a standard EEG cap and conductive gel to ensure the conductivity of the electrodes with the scalp. Nine more electrodes attached in different places to measure EOG, ECG, GSR and EMG were also used. The sampling rate for those electrophysiological recordings was set to 2048 Hz. A more analytical explanation of the protocol follows below.

5.4.1 Self Report questionnaires

Participants were asked to fill in a self-report questionnaire at the end of each task during the whole experiment, where they evaluated their different emotional levels (in a scale of 0 to 7) according to the different tasks. The self-report questionnaires included 'Joy', 'Sadness', 'Rage', 'Surprise', 'Anxiety', 'Disgust' and 'Relax'.

5.4.2 Electrophysiological recordings

For EEG recordings, 32 electrodes have been placed in the scalp of each participant following the 10-20 system (Figure 1.2). 9 external electrodes have also been used:

- External 1: right mastoid (reference)
- External 2: Vertical left eye movements
- External 3: Horizontal left eye movements
- External 4: Left wrist
- External 5: Corrugator 1 internal (above left eye)
- External 6: Corrugator 2 external (above left eye)
- External 7: Zigomatic 1 (left cheek)
- External 8: Zigomatic 2 (left cheek)
- External 9: Galvanic Skin Response

After the head cap with the 32 electrodes and the external electrodes were placed on the participant, the data acquisition began.

5.4.3 Procedure

The physiological electrical activity of each participant has been recorded through spontaneous EEG, ECG, EOG, EMG and GSR.

The recording time was about 50 minutes, plus approximately 40 minutes required for the attachment of the electrodes to the participant. The total time of an experiment was thus about 90 minutes.

The room where the experiments took place was big enough to host 4 persons comfortably seated and the recording equipment, the monitors and the two researchers who run the experiments. A variety of tasks were defined in order to capture a range in stress levels. Since EEG is very time-consuming on set up, a pilot test was run using just the tasks and the subjective rating scales, to confirm that a range in stress levels is actually captured.

A number of spectators (actors) have been used in order to induce social stress according to Kirschbaum et al. [107].

5.4.3.1 Spontaneous EEG + ECG + EOG + EMG + GSR (50 minutes)

The ActiveView software has been used for the acquisition of the data. This is the standard software to run the Biosemi ActiveTwo hardware, and it is based on the commercial package LabView.

The recordings of spontaneous EEG, ECG, EOG, EMG and GSR have been performed using all electrodes (head cap, external electrodes and GSR electrodes), at a sampling rate of 2048Hz. The participants were asked to sit in a comfortable chair and the researchers placed the cap and the electrodes. The external electrodes were placed using special stickers to ensure the conductivity of the electrodes with the skin. The participants had to remain seated during the whole experiment.

A commercial application called "Presentation" was used to mark all the different trials (tasks) for further analysis of the signals. This SW also provided instructions to the participants for each one of the tasks. The Stroop test and the Read task were also displayed using this SW. The participants were asked to perform several tasks that are described in the following lines:

Baseline Recording (3 min) The participant had to stare at a white screen for 3 minutes.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Relax (4 min) The participant had to close his/her eyes and relax for 4 minutes.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Stroop Test (4 min) The participant had to perform a Stroop Test for 4 minutes. The Stroop test consists of reading aloud the names of some colours, but the colours of the text are not the same with the names they read.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Mathematical Task (4 min) The participant had to count down from a large prime number (2039) in decrements of 13 as quickly and as accurately as possible, for 4 minutes. For some people this task has been shown to be quite frustrating and stressing.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Read Task (4 min) The participant had to read a detective tale as fast and as concentrated as possible for around 4 minutes. The participant is falsely told that a test will be made afterwards to measure the attention he/she paid to the text. The average reading speed of a university student is about 240 words per minute. The detective tale that the participant should read has about 1000 words.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Supervised Baseline Recording (3 min) Three persons were introduced to the participant and presented as especially trained to monitor non-verbal behaviour and that they will be present for the rest of the experiment. Besides, a camera and a microphone were also placed in the recording room. The participants were told that a voice frequency analysis would be performed on the tape-recorded talk. The participants were also told that a similar analysis would be performed with the video. The participant has to stare at a white screen for 3 minutes.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Supervised Relax (4 min) The participant had to close his/her eyes and relax for 4 minutes.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Supervised Stroop Test (4 min) The participant had to perform a Stroop Test for 4 minutes. This test was similar to the previous one.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Supervised Mathematical Task (4 min) The participant had to count down from a large prime number (2803) in decrements of 17 as quickly and as accurately as possible, for 4 minutes. Notice that the initial and the decremental numbers are different than the previous mathematical task. That was done in order to avoid habituation.

Questionnaire (1 min) The participant has to fill in a quick self-report questionnaire.

Supervised read Task (4 min) The participant had to read a detective tale as fast and as concentrated as possible for around 4 minutes. The text is different that the previous read task. Again, The participant is falsely told that a test will be made afterwards to measure the attention he paid to the text.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Fake blood sample collection (3 min) The participant was told that a blood sample was required to finalise the experiment. An male nurse appeared holding a big syringe and

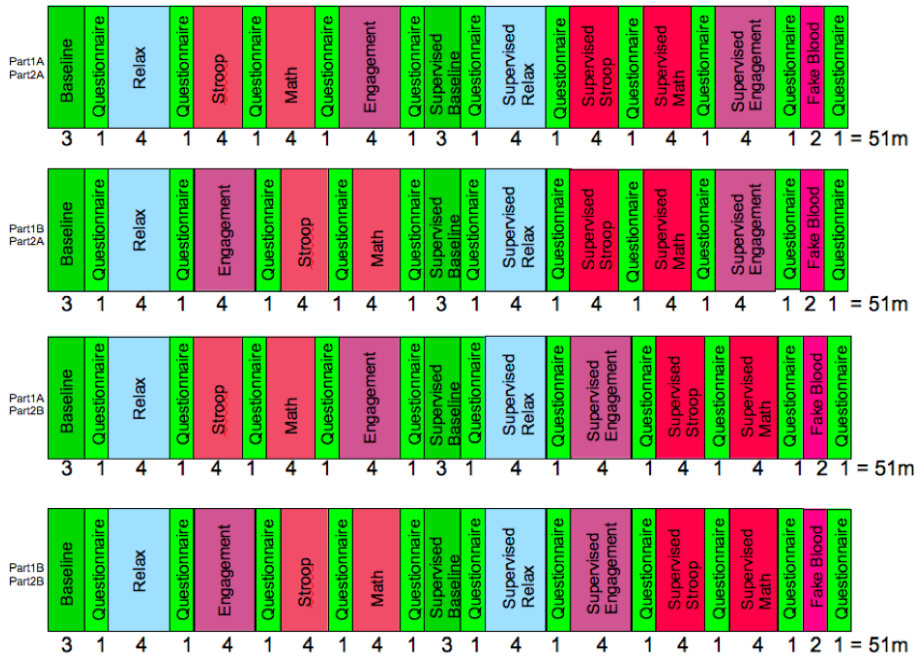

Figure 5.1: Schematic representation of the protocol used in the data recording

a holder with several fake blood samples (to make it more realistic). The male nurse placed an elastic band around the arm of the participant and acted like actually performing the blood sample collection. At the last moment the participant was told that the sample was not needed.

Questionnaire (1 min) The participant had to fill in a quick self-report questionnaire.

Figure 5.1 shows the schematic representation of the protocol that was used on the data recording. There are 4 different protocol representations due to the interchange of the order of the tasks read in the first part, in the second part, or on both parts. This was done to randomise the order of tasks in order to avoid conditioning effects through participants.

Figure 5.2 shows the experimental set-up with the 3 actors sitting around the table and the male nurse actor that performs the fake blood sample standing up in front of the participant.

5.5 Data Analysis and Results

5.5.1 Data Pre-Processing

There are 41 channels (32 EEG channels plus 9 external electrodes) at a sampling rate of 2048. The first step is to reference the different channels.

- The EEG channels (from 1 to 32) are referenced to the Cz. The reason to do that is because a good feature to study after the literature review is the Alpha Asymmetry and this is achieved by referencing to Cz (Gotlib et al. [106]).

Figure 5.2: Ongoing Experiment with participant and actors

- EOG vertical and horizontal channels (34 and 35) are referenced to the right mastoid.
- The ECG channel (36) is referenced to the right mastoid as well.
- EMG channels are bipolar leads so we have that EMG corrugator is obtained by doing channel 37 - channel 38. EMG zigomatic is obtained by doing channel 39 - channel 40.
- Finally the GSR channel (41) does not need referencing, although the mean was subtracted in order to remove the offset.

The list of the 38 channels:

- channel 1 to 32: EEG
- channel 33: vertical EOG
- channel 34: horizontal EOG
- channel 35: ECG
- channel 36: Corrugator EMG
- channel 37: Zigomatic EMG
- channel 38: GSR

As the signal has 50 Hz line noise, a notch filter and a band pass filter have been applied from 1 to 40 Hz to the EEG channels. The EMG channels are also notch filtered but in this case the band pass is from 20 to 200 Hz. Finally the GSR channel was not filtered. The next step in pre-processing is to cut the data in the corresponding task periods. As the protocol sent triggers to the Biosemi system using the Presentation commercial package, this was easily achieved. The result is 5 epochs for the non-supervised task corresponding to:

- Baseline1 (BL1)
- Relax1
- Stroop1
- Math1
- Read1

and 6 epochs for the supervised tasks corresponding to:

- Baseline2 (BL2)
- Relax2
- Stroop2
- Math2
- Read2
- Blood Sample2 (blood2)

The GMCturbo EOG artefact corrector algorithm was applied on each one of these epoch for the EEG channels in order to correct the ocular artefact. This is an algorithm that subtracts a fraction of both the vertical and horizontal EOG channels to each one of the EEG channels. The fractions that are subtracted are computed by minimising the energy of:

$$\vec{S_{cor}} = \vec{S} - k_1\vec{V} - k_2\vec{H} \tag{5.1}$$

The channels of interest is the EEG channel $\vec{S}$, $\vec{V}$ the vertical EOG component and $\vec{H}$ the horizontal EOG component. k_1 and k_2 are the expected fractions. For a deeper explanation of this EOG corrector method, please refer to section 4.3.1.

The EEG signal has been cut in 50% overlapping 2-second epochs. The features (Alpha Assymetry and Beta/Alpha ratio) have been extracted from each one of those 2 second epochs. If any value of each of these epochs is higher or lower than a certain threshold (th=40 μV), the whole epoch is discarded. In this way the use of epochs with strong artefacts is avoided. In any case, less than 5% of the epochs of each task is discarded in all cases.

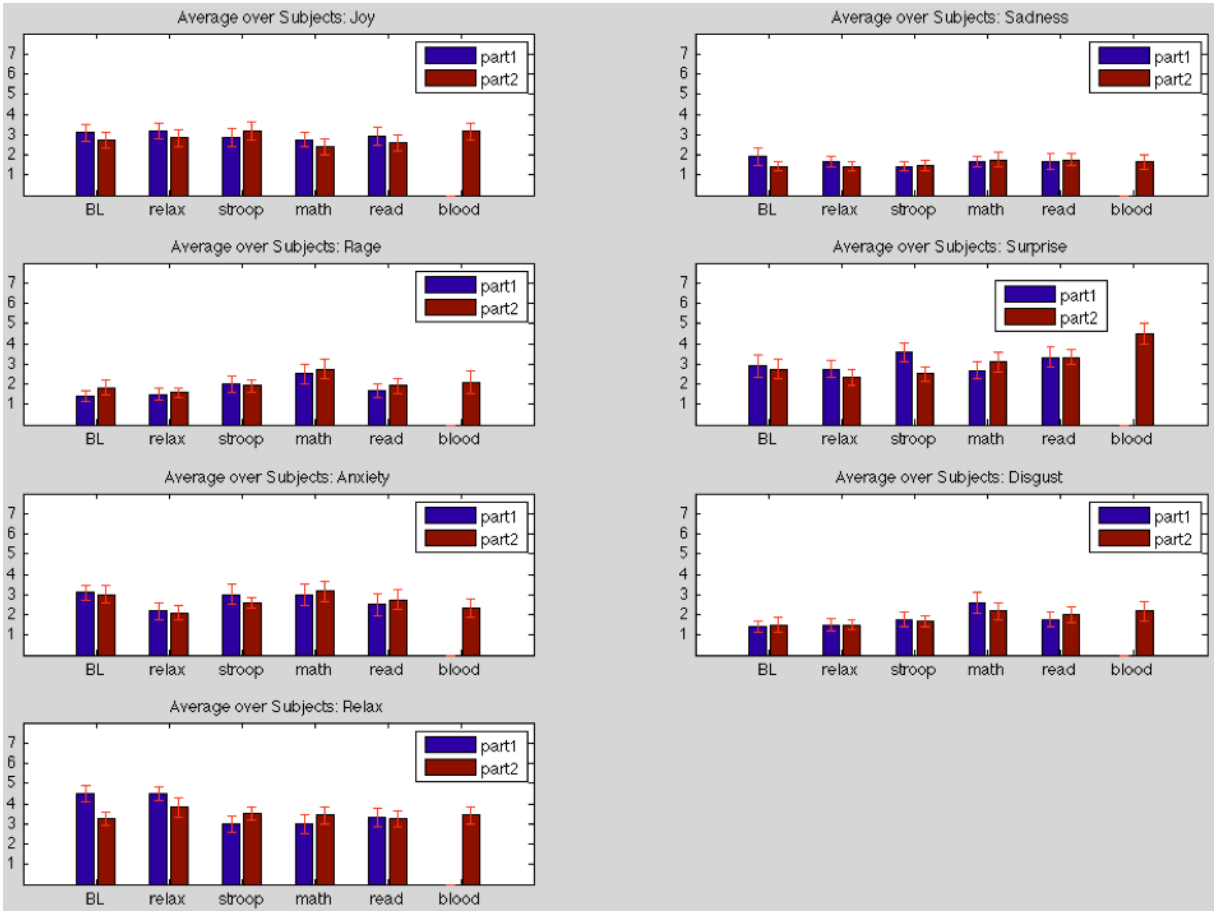

Figure 5.3: Self Report Questionnaire Results

5.5.2 Self Report Questionnaire Analysis

Figure 5.3 shows the result of the mean over participants of the self-report questionnaires. The figure depicts the value between 1 and 7 of different feelings such as joy, sadness, rage, surprise, anxiety, disgust and relax (note that the standard deviations are divided by the square root of the number of participants).

Some interesting observations can be extracted from the above figures. The first thing we notice is that the participants feel less Joy in the second part of the recording (when the actors are present) in every task except in the Stroop test. The same happens with the relax feeling for the Baseline and Relax tasks. It can be said that the presence of the actors does affect, at least as a tendency, the feelings of the participants. A peak can also be seen in the surprise figure during the Fake Blood Sample task. Finally, the negative feelings are stronger in the Stroop and Math task (Rage, Anxiety and Disgust) and the Relax feeling decreases as well during the experiment. This information will be used as a ground truth and correlations with the EEG features will be extracted in the sections 5.5.4 and 5.6.

It is important to understand that this data is subjective: the participant rates his/her own feelings. There are some effects that occur such as habituation: the second time the participant performs a task, the level of Surprise, for instance, decreases (except in the case of the Math task). This effect can be observed in the precedent figure.

A Student's t-test has been applied to the self-report questionnaires. The result of this statistical test can be found in the tables of section 5.8, where the tasks that with meaningful statistical differences ($p < 0.05$) are indicated.

As an example, for the Surprise feeling, we find meaningful statistical ($p < 0.05$) between Stroop2 and Blood Sample, for Anxiety between Baseline1 and Blood Sample and finally for Relax between Baseline1 and Stroop1. There are many more statistical differences between other tasks (refer to section 5.8), but we will focus on the tasks we have just described (Baseline1-2, Stroop1-2 and Blood Sample), in the classification study presented in section .

5.5.3 Peripheral Sensors

Figure 5.4 presents the evolution over tasks of the features extracted from the peripheral sensors:

- GSR (mean and number of events per time unit)
- EMG (corrugator and zigomatic energy per time unit)
- ECG (Heart Beat Rate)

It represents the mean over the 12 participants of the evolution of the different physiological measure over the different tasks (the standard deviation is divided by the square root of the number of participants).

Once more, there are some interesting observations hidden in these plots. Regarding the GSR (events per minute) a minimum in the Relax task can be observed, then it increases in Both Stroop and Math task. It decreases again in the Reading task to finally increase again in the Fake Blood Sample task. This behaviour is expected and thus it seems that the GSR is a good indicator of stress. The presence of actors seemed to affect the Baseline and the Relax tasks also. The same conclusions can be extracted with the mean GSR figure. The zigomatic EMG plot show a maximum in the Fake Blood Sample task and two local maxima in the 'stressful' tasks Stroop and Math. The results in the corrugator EMG plot are similar. A local maximum in the Read task also occurs in this case. This might be due to the fact that the participant is moving his/her eyes while reading, thus contributing to the corrugator energy. Finally, the tasks Stroop, Math and Fake Blood Sample have a higher HBR than the rest of the tasks.

The above results were expected, therefore, it can be said that the experimental protocol is suited to induce stress feelings. The information gathered in this section is objective data, so somehow it is more valuable than the subjective data gathered with the questionnaires in the precedent section. Once again, this information will be used as a ground truth and correlations with the EEG features will be extracted in the next section.

Again, a Student's t-test has been applied to the features extracted from the peripheral sensors. As in this case most of the tasks are statistically different ($p < 0.05$), we do not provide a summary in this section, but the interested reader can find all the information in the tables of section 5.8

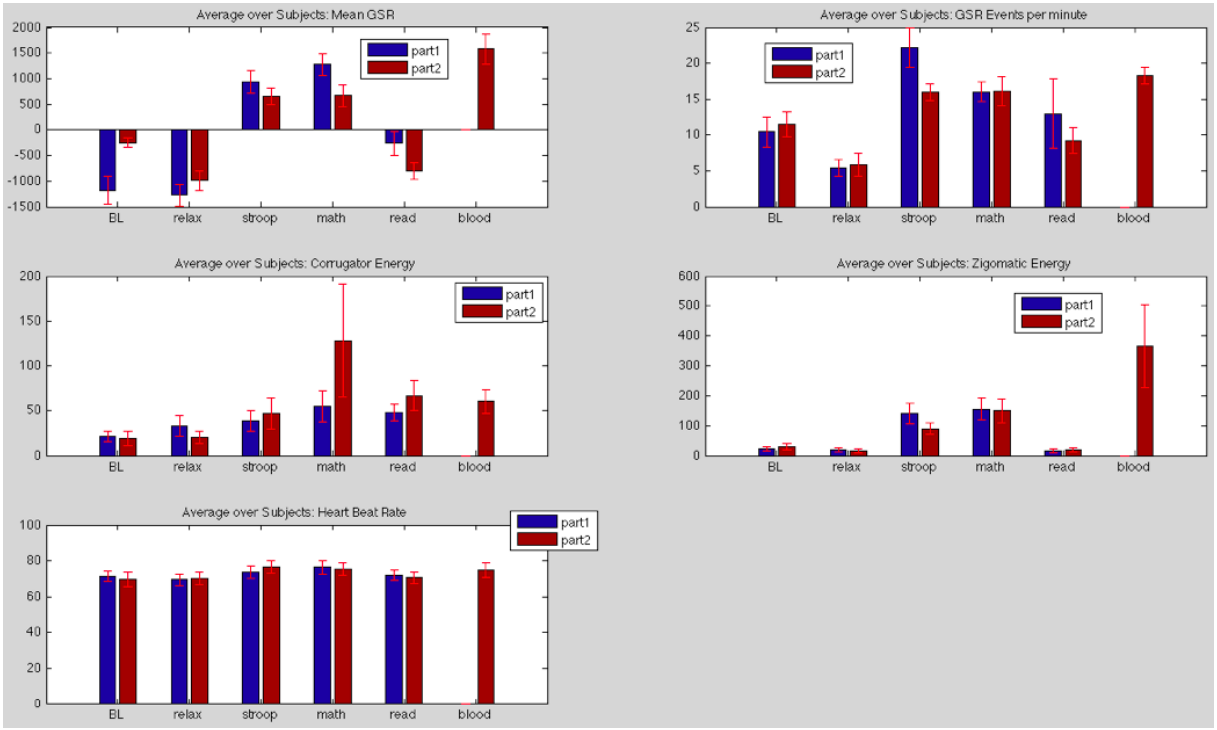

Figure 5.4: Peripheral Sensors Results

5.5.4 EEG data analysis

The main objective of this research is to find stress markers in the EEG signal. As explained before, 32 EEG channels have been recorded using the BIOSEMI ActiveTwo amplifier. In this analysis only the frontal channels F3, F4, F7 and F8 have been used. The reference is placed in Cz. The reason to focus on these electrodes is because it would allow the use of the ENOBIO sensor, which is much less obtrusive than standard EEG recording devices. This sensor, developed by Starlab Barcelona SL, is a wireless wearable EEG recording device that uses 4 channels. Its configuration allows placing the electrodes anywhere on the head, but after reviewing the literature, the Alpha Asymmetry works better in the frontal cortex. Figures 5.5 and 5.6 shows the ENOBIO sensor in its cap configuration.

In our work we have focused on two features: Alpha Asymmetry and Beta/Alpha ratio. There are many Alpha Asymmetry studies (for instance Gotlib et al. [106] and Lewis et al. [53]) in which it has been found that positive moods or reactions predict relatively greater left prefrontal activity (i.e. less left alpha) while negative moods or reactions predict relatively greater right prefrontal activity. In other words, Alpha Asymmetry is an good indicator of the valence dimension of emotions. The following operation has been performed to compute the Alpha Asymmetry:

Our hypothesis is that stress is related with a negative mood and no-stress is related with a positive mood.

$$Alpha\ Asymmetry\ =\ Left\ Alpha\ Power\ -\ Right\ Alpha\ Power \tag{5.2}$$

Figure 5.5: Side view of the ENOBIO sensor in its EEG cap configuration

Figure 5.6: Frontal view of the ENOBIO sensor. The data acquisition software can also be seen

The Beta/Alpha ratio has been related with to the arousal dimension of emotions (see Zhang and Lee [44] and Bos [111]). High values of Beta/Alpha Ratio indicate high level of arousal, and vice versa. Beta/Alpha Ratio has been computed as follows:

$$Beta/Alpha\ Ratio\ =\ Beta\ Power\ /\ Alpha\ Power\ (of\ the\ same\ channel) \tag{5.3}$$

Figure 5.7 shows both the Alpha Asymmetry for two different configurations: F3 vs. F4 and F7 vs. F8. The plot shows the mean of this feature over participants for each task. The standard deviations are divided by the square root of the number of independent samples (standard deviation of the mean).

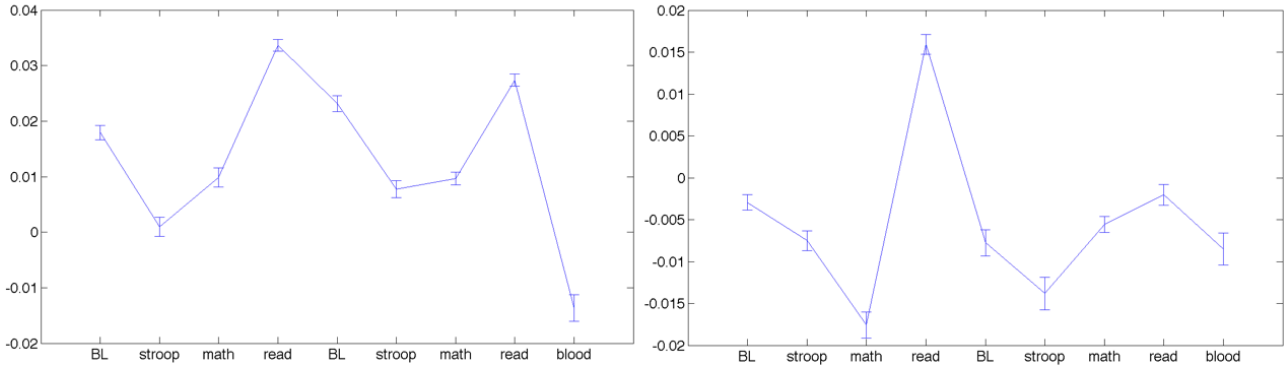

Figure 5.7: Alpha Asymmetry evolution over tasks. In the left figure for the pair of channels F7 and F8, in the right for F3 and F4. The error bars represent the standard deviation of the mean

Some interesting trends can be observed in both figures depicted in 5.7. Regarding the left plot (F7-F8 configuration), the Alpha Asymmetry is relatively higher in the Baseline and Read tasks and relatively lower in the 'stressful' tasks (Stroop and Math). A negative peak is also observed in the Fake Blood Sample task. If we consider the Baseline and Read tasks the less stressing ones, Stroop and Math as moderately stressing and finally the Fake Blood Sample task as the most stressing one, a clear correlation between stress level and Alpha Asymmetry is unveiled.

Regarding the right plot of 5.7 (F3-F4 configuration) something similar can be observed. In this case the first Read task has a very high Alpha Asymmetry and the Fake Blood Sample task is not as low as before, but the trends are also observed.

In the plots presented in figure 5.8 we depict the evolution of the mean over participants of the Beta/Alpha ratio over tasks for each one of the channels F3, F4, F7 and F8.

The Beta/Alpha ratio of the Fake Blood Sample task presents an important maximum as well. In the plots of channels F4 and F8 (figure 5.8) we can see the Stroop and Math tasks between Baseline and Blood tasks. If we consider the Baseline and Read task the less stressing ones, Stroop and Math as moderately stressing and finally the Fake Blood Sample task as the most stressing one, a clear correlation between stress level and Beta/Alpha ratio is unveiled. This behaviour is similar to the one observed with the Alpha Asymmetry feature (figure 5.7).

In general, we did not find significant differences between our EEG features (both Alpha Asymmetry and Beta/Alpha ration) between the first part of the experiment (no actors) when compared to second part (with actors). It is not possible to conclude that the presence/absence of actors affects our EEG features.

In Figure 5.9 we can see the Alpha Asymmetry (between F7 and F8) plotted against the Beta/Alpha Ratio (of F7). The averages values among all participants for each task have been plotted.

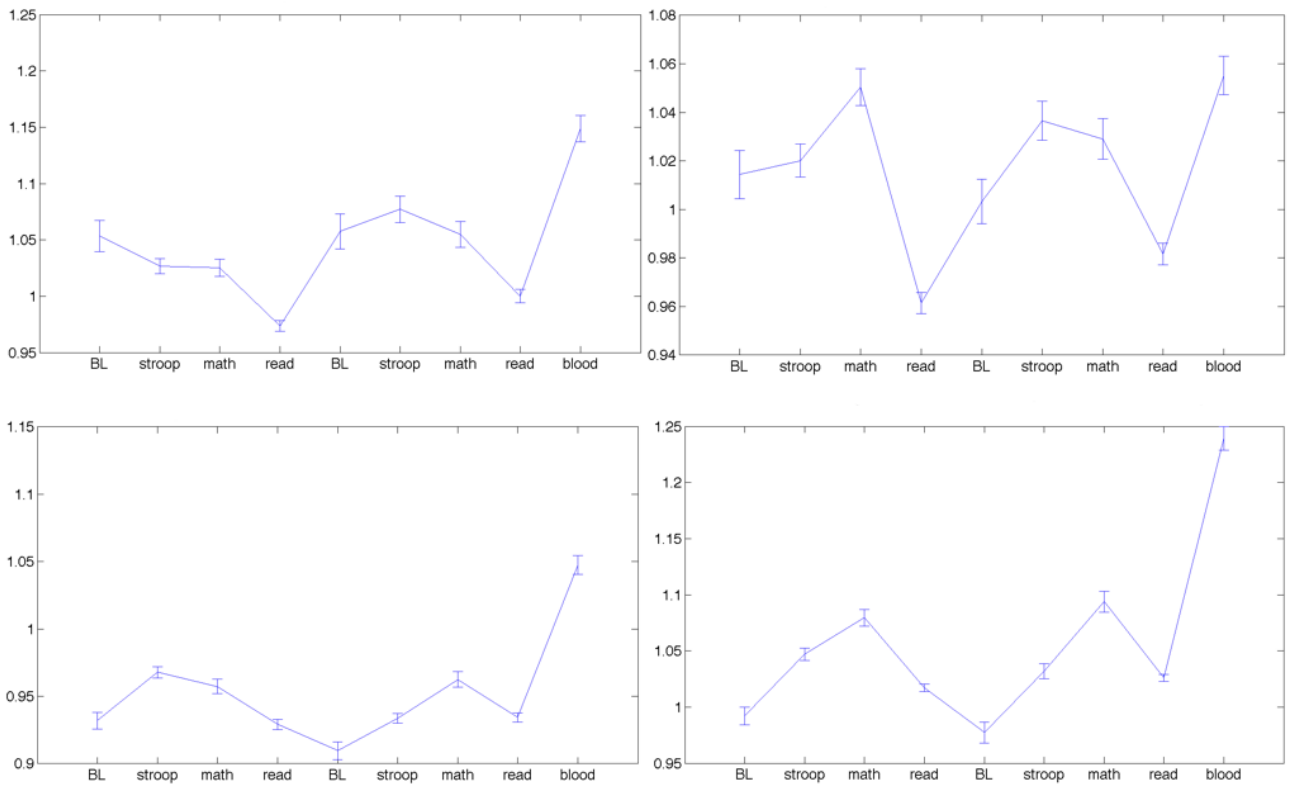

Figure 5.8: Beta/Alpha ratio evolution over tasks. Clockwise and starting from the upper left figure for the channel F7, F3, F8 and F4 respectively. The error bars represent the standard deviation of the mean

The trend observed in that plot shows the expected results. In general, a clear relation between the Alpha Asymmetry and the stress level of the tasks can be seen. The same applies to the Beta/Alpha Ratio. We can also see that the tasks with or without actors tend to cluster together. This indicates two interesting things. On the one hand we see that our results are robust in the sense of repeatability. On the other hand the presence of the actors does not affect in the EEG features significantly.

The EEG features for the Relax task have also been presented in figure 5.9 for completeness. But it is important to remember that during this task, participants kept their eyes closed. It is a well-known fact that the alpha rhythm significantly increases in this condition and thus it would be unfair to compare eyes closed EEG with eyes open EEG. That is why, for the rest of the analysis we will focus only on the eyes open tasks.

It should be mentioned that the results presented in this section are based on averages over participants. We have noticed an important inter-subject variability. Our next challenge is to extract the level of stress (as a function of valence and arousal) from EEG but on a subject-to-subject basis. This work is presented in section 5.6, where we applied machine learning techniques and we achieved quite a good classification performance.

The last figure of this section involves the correlations between the different variables of the 2 EEG features, the 7 feelings of the self-report questionnaire and the 5 recorded peripheral signals. The correlation coefficient of (as an illustrative example) Alpha Asymmetry (over the

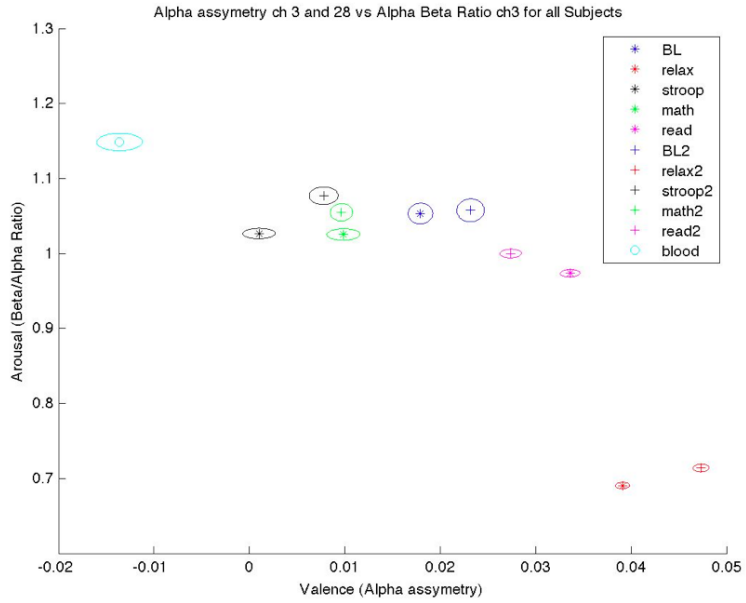

Figure 5.9: Mean Alpha Asymmetry (F7-F8) vs. mean Beta/Alpha ratio (F7) per task. The ellipses represent the standard deviation of the mean of both features. Please note that participants kept their eyes closed during the Relax tasks

11 tasks) and the GSR mean (over the same 11 tasks as well) have been computed in order to conclude if the variation of both magnitudes are correlated, anti-correlated, or even if they are independent.

		Alpha Asym	Beta/Alpha	Joy	Sadness	Rage	Surprise	Anxiety	Disgust	Relax	Mean GSR	GSR events	Corrugator	Zigomatic	Heart Beat
EEG	Alpha Asym	1													
	Beta/Alpha	-0.83	1												
Questionnaires	Joy	-0.1	-0.1	1											
	Sadness	-0.08	0.2	-0.01	1										
	Rage	-0.57	0.48	-0.61	0.05	1									
	Surprise	-0.63	0.5	0.1	0.22	0.19	1								
	Anxiety	-0.42	0.64	-0.53	0.25	0.5	0.01	1							
	Disgust	-0.52	0.42	-0.4	0.24	0.84	0.35	0.28	1						
	Relax	0.43	-0.52	0.52	0.41	-0.65	-0.29	-0.35	-0.61	1					
Peripheral S.	Mean GSR	-0.85	0.66	-0.07	-0.19	0.75	0.47	0.28	0.72	-0.7	1				
	GSR events	-0.88	0.75	-0.07	-0.15	0.61	0.54	0.48	0.5	-0.66	0.89	1			
	Corrugator	-0.37	0.35	-0.58	0.37	0.82	0.29	0.33	0.66	-0.34	0.45	0.37	1		
	Zigomatic	-0.86	0.55	0.13	0.03	0.57	0.71	0.03	0.63	-0.36	0.85	0.7	0.41	1	
	Heart Beat	-0.76	0.61	-0.02	0.07	0.73	0.2	0.32	0.68	-0.46	0.86	0.77	0.55	0.67	1
		EEG		Questionnaires							Peripheral sensors				

Figure 5.10: Correlation analysis between EEG, self-report questionnaires and peripheral sensors. We have highlighted in yellow the features that have statistically significant ($p < 0.05$) correlations or anti-correlations

In Figure 5.10, the correlation values that have a corresponding p-value equal or lower than 0.05 have been highlighted. These highlighted values can be considered to have a significant correlation (or anti-correlation if the correlation value is negative). Note that the correlation

coefficient has commutative property: corr(A.B)=corr(B.A) so the table above contains a symmetrical matrix, and only its inferior part is shown.

This table provides very interesting information i.e. significant anti-correlation between Alpha Asymmetry and Beta/Alpha Ratio, Surprise, Mean GSR, GSR Events, Zigomatic EMG and Heart Beat

A similar behaviour can be observed with Beta/Alpha Ratio, but in this case there is a significant positive correlation with Alpha Asymmetry (anti-correlation), Anxiety, Mean GSR, GSR events and Heart Beat.

These results are very interesting for our work, since they prove there is a correlation between EEG extracted features and both subjective questionnaires and other independent physiological signals. Regarding the self-report questionnaires, the correlation of Beta/Alpha Ratio with Anxiety is quite significant, since the Anxiety emotion can be easily linked with stress. Regarding the other physiological features, both Alpha Asymmetry and Beta/Alpha Ratio correlates with Mean GSR, GSR Events and Heart Beat. It is well know that GSR and HBR are the most common measure used in emotions studies. We consider these results quite consistent and remarkable, and also encouraging as demonstrating that EEG can be used to evaluate stress.

Most of the correlations from figure 5.10 are intuitively expected. For instance, it is normal that Joy and Rage are anti-correlated. It is also not surprising that Surprise and Zigomatic are correlated: when something surprises us we tend to change our facial expressions, and thus incrementing the Zigomatic Energy. Relax is anti-correlated with Mean GSR and GSR events, proving that GSR is a good indicator of stress. Similar argumentations can be applied to the rest of the correlations.

Some other interesting correlations for the peripheral sensors are found between Mean GSR, GSR events and Heart Beat Rate.

As a summary of this correlation study, the important conclusion is that Alpha Asymmetry is anti-correlated with Mean GSR, GSR events and Heart Beat rate. Beta Alpha Ratio is also correlated with the same physiological recordings. This means that through EEG we are able to extract information related with the stress level of the subjects in each one of the tasks, at least when working with averages over subjects. In the next section we will aim for a more ambitious objective: we will work on a subject to subject basis and attempt to classify the different stress levels of the subjects using only the EEG features.

5.6 Classification using EEG

In the previous sections group averages over participants were used. By doing so, interesting trends between the different tasks were successfully found. Although this work brings some light about how stress can be measured using EEG, it does not allow us to build an application where stress can be detected through EEG on a subject to subject basis. This is the reason why machine learning techniques, i.e., classifiers, were applied to our dataset. We have applied these techniques to several classification problems.

Intuitively we can define a stress level to each one of our tasks: Baseline and Read have a low stress level, Stroop and Math a moderate stress level and Fake Blood Sample a high stress level. Note that the Relax task is excluded from this analysis since, as mentioned before, the participants kept their eyes closed and thus affected their EEG features.

This subjective stress level assignation to our different tasks is partly supported by the results of our physiological peripheral sensors and by the self-report questionnaires. For instance the GSR features and the HBR is smaller for Baseline/Read, then it increases to comparable levels for Stroop/Math, and have a maximum for Fake Blood Sample task (figure 5.4). Similar considerations can be one from the Relax, Disgust, Surprise and Rage feelings from the self-report questionnaires (figure 5.3).

More precisely, Number of GSR events is statistically different ($p < 0.05$) between Baseline1, Stroop2 and Fake Blood Sample tasks. The same applies to the tasks Baseline2, Stroop2 and Fake Blood Sample. This can be seen in table 5.9. We will focus on these tasks.

The classifier used was Fisher Discriminant Analysis (FDA) with DF Quadratic. The EEG feature vectors have 3 components (Alpha Asymmetry chX-chY; Beta-Alpha ratio chX; Beta-Alpha ratio chY) and only the aforementioned tasks of the second part of the experiment, when the actors were present, are used. In order to perform the classification, a cross-fold validation using the leave-one-out approach was used: all the features from participant 1 are used for the test set and the features of the remaining 11 participants for the training set, then all features from participant 2 are used for the test set and the rest of the participants are used for the training set and so on.

The output of the LDA classifier is a Posterior Matrix, i.e., a vector of probabilities that a given feature vector belongs to any one of the available classes. This vector of probabilities is in fact a discrete Probability Density Function with sum equal to one. Each participant has a different number of feature vectors for each class due to the artefact removal step (a step described in the EEG data analysis section, where noisy epochs were removed) and due to the fact that the Fake Blood Sample task took a different amount of time for each participant. In any case the task that had fewer epochs was Fake Blood Sample task with a mean of 112.1 $\pm$ 31.0 epochs. The way the performance is computed is done by applying a mean to the Posterior Matrix for all the epochs of a given task, and then choosing the maximum's location as the result of the classification. As an example of the different 2-class problem (Baseline1 vs Fake Blood Sample, for instance), if the maximum of the mean of the posterior matrix (2 component vector) appears in the first component, the chosen class would be Baseline and if it appears in the second component, the chosen class would be Fake Blood Sample. This was performed for all the participants and for all the tasks. In the case of 2 classes, 24 classification results are obtained (12 participants *2 different tasks). For each result, all the EEG information available for the given tasks is used by fusing the posterior matrix using the mean operator, as explained above.

As 32 channels were recorded , 14 pairs of symmetric channels can be build (FP1-FP2; AF3-AF4; F7-F8; F3-F4; FC1-FC2; FC5-FC6; T7-T8; C3-C4; CP1-CP2; CP5-CP6; P7-P8; P3-P4; PO3-PO4 and O1-O2). The performance of the classification algorithm for the features extracted for each one of these pair of channels are shown in Table H.6.

From Table H.6 we see that in the case of Baseline1 vs Stroop2, a performance of 75% is reached in the following pair of channels: P7-P8 (performance equal to 83% for Baseline2 -

	FP1-FP2	AF3-AF4	F7-F8	F3-F4	FC1-FC2	FC5-FC6	T7-T8	C3-C4	CP1-CP2	CP5-CP6	P7-P8	P3-P4	PO3-PO4	O1-O2
Baseline1-Stroop2	54	54	58	58	54	54	63	58	50	63	**75**	63	58	46
Baseline2-Stroop2	63	58	67	50	50	50	58	50	54	67	**83**	71	63	50
Baseline1-Blood	71	67	79	63	46	**88**	67	67	50	71	58	38	42	42
Baseline2-Blood	71	71	79	67	50	79	67	71	58	**83**	58	42	46	46
Stroop2-Blood	63	67	58	58	54	63	63	58	38	75	**79**	63	58	38

Table 5.1: Performance in percentage for each classification problem (3 2-class problems) and for each pair of symmetric channels. The best performance for each one of the classification problems is highlighted in bold

Stroop 2 for the same pair of channels). In that case, a random classification would yield a performance of 50%, so the classification is still far above random classification. Regarding Baseline1 vs Blood classification, a performance of 88% is reached in the frontal pair of channels FC5-FC6 (performance equal to 83% for Baseline2 - Blood for the pair CP5-CP6). Finally, a classification of 79% is reached in the case of Stroop2 vs Blood for the pair P7-P8.

Some other interesting classification results includes a performance of 79% for Baseline1-Stroop1 (P7-P8), 79% for Baseline1-Math1 (FC5-FC6) and 79% for Stroop1-Blood (FC5-FC6). It is also worth to mention that when comparing the Relax vs Blood, we reach an almost perfect classification (96%) in the posterior/occipital channels pairs (P3-P4, PO3-PO4 and O1-O2). As mentioned earlier, this is with no doubt due to the fact that the participants had their eyes closed during the Relax task and these results should not be considered as relevant from the point of view of stress detection since we are rather detecting if the participants have their eyes open or eyes closed.

This system could be easily implemented using only 3 channels (a pair of symmetric channels plus Cz as reference) and applied in many applications such as Augmented Reality or Virtual Reality Environments. For instance the virtual scenario could adapt according to the stress level of users.

5.7 Conclusion and Discussion

This chapter describes the protocol and the experiments that have been performed at Starlab Barcelona SL premises together with the processing steps.

There are 3 different sets of data recorded:

1. Self-report questionnaires (Subjective)
2. Peripheral sensors (Objective). Those sensors include EOG, ECG, EMG and GSR but not EEG

3. EEG data (Objective)

The first two sets of data have been used as ground truth. The undertaken research was aimed at searching meaningful correlations between the features extracted from the EEG recordings and the 2 other data sets.

Stress markers in the EEG signal have been investigated. For this reason, a protocol has been designed in order to induce stress to the participants. One of the ideas was to have 3 actors supervising the experiments to induce social stress to the participants, but as we have seen, the presence of actors did not significantly increase the stress level of the participants. On the other hand, the tasks designed to generate stress such as Math, Stroop and Blood Sample did show significant differences in the 3 recorded data sets.

The EEG features plotted one against the other (Alpha Asymmetry versus Beta/Alpha Ratio) revealed a clear correlation between the levels of stress of the designed tasks. This was easily seen by performing an average over participants. It was also found that there is an important inter-subject variability.

A series of correlation studies were also performed and very interesting results were found. Interesting trends between different variables were found. Mainly, the subjective questionnaires and the peripheral signals, which were recorded as a ground truth, show strong correlations with the extracted EEG features.

In the second part of this work, computational intelligence techniques such as classification and fusion algorithms were applied to identify the stress level of the participants on a subject to subject basis. We have compared between different pairs of conditions and all of them showed encouraging results. As a summary we have reached a performance up to 88% for Baseline1 - Blood, 83% for Baseline2 - Stroop2 and also for Baseline2 - Blood 79% for Stroop2 - Blod and finally 75% Baseline1 and Stroop2.

The results of this research show that using only 2 EEG channels (plus a reference in Cz) would provide enough information for the system to work with this performance. Another interesting and important characteristic of this work is that all the data processing steps can be performed in near real-time, thus allowing this system to work in several applications such as neurofeedback and augmented reality in virtual telepresence.

The final conclusion of this study is that it is possible to measure stress with EEG signals. Moreover, it is important to note that only 2 electrodes were used (plus an active reference in Cz). So a system ready to measure stress using only 3 electrodes has proven to work well in the conditions describe in this work, which means that the ENOBIO amplifier could be used for such a system.

5.8 Statistical Analysis of the Self Report Questionnaires and the Peripheral Sensor Features

5.8.1 Self Report Questionnaires

The following tables shows the results of a Student's t-test applied to each one of the self-report emotions between each task. The X marks indicates meaningful statistical differences ($p < 0.05$) between the tasks. Note that the matrices are symmetric.

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-										
Relax1		-							X	X	
Stroop1			-								
Math1				-							
Read1					-				X		
BL2						-			X		
Relax2							-				
Stroop2								-			
Math2		X			X	X			-		
Read2		X								-	
Blood											-

Table 5.2: Student's t-test applied to the Joy self-reported levels between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-			X					X		
Relax1		-		X					X		
Stroop1			-								
Math1	X	X		-	X	X	X			X	
Read1				X	-				X		
BL2				X		-			X		
Relax2				X			-		X		
Stroop2								-	X		
Math2	X	X			X	X	X	X	-		
Read2				X						-	
Blood											-

Table 5.3: Student's t-test applied to the Rage self-reported levels between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-						X				X
Relax1		-									X
Stroop1			-				X	X			
Math1				-							X
Read1					-		X				
BL2						-					X
Relax2	X		X		X		-			X	X
Stroop2			X					-			X
Math2									-		X
Read2							X			-	X
Blood	X	X		X		X	X	X	X	X	-

Table 5.4: Student's t-test applied to the Surprise self-reported levels between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-	X					X				X
Relax1	X	-	X			X			X		
Stroop1		X	-								
Math1				-							
Read1					-						
BL2		X				-	X				
Relax2	X					X	-	X	X		
Stroop2							X	-			
Math2		X					X		-		
Read2										-	
Blood	X										-

Table 5.5: Student's t-test applied to the Anxiety self-reported levels between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-			X					X		
Relax1		-		X							
Stroop1			-								
Math1	X	X		-			X				
Read1					-						
BL2						-			X		
Relax2				X			-				
Stroop2								-			
Math2	X					X			-		
Read2										-	
Blood											-

Table 5.6: Student's t-test applied to the Disgust self-reported levels between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-		X	X		X		X		X	X
Relax1		-	X	X	X	X		X		X	X
Stroop1	X	X	-								
Math1	X	X		-							
Read1		X			-						
BL2	X	X				-					
Relax2							-				
Stroop2	X	X						-			
Math2									-		
Read2	X	X								-	
Blood	X	X									-

Table 5.7: Student's t-test applied to the Relax self-reported levels between each condition

5.8.2 Peripheral Sensors

The following tables shows the results of a Student's t-test applied to each one of the peripheral sensor features between each task. The X marks indicates meaningful statistical differences ($p < 0.05$) between the tasks. Note that the matrices are symmetric.

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-		X	X	X	X		X	X		X
Relax1		-	X	X	X	X		X	X	X	X
Stroop1	X	X	-		X	X	X			X	X
Math1	X	X		-	X	X	X	X	X	X	
Read1	X	X	X	X	-		X	X	X	X	X
BL2	X	X	X	X		-	X	X	X	X	X
Relax2			X	X	X	X	-	X	X		X
Stroop2	X	X		X	X	X	X	-		X	X
Math2	X	X		X	X	X	X		-	X	X
Read2		X	X	X	X	X		X	X	-	X
Blood	X	X	X		X	X	X	X	X	X	-

Table 5.8: Student's t-test applied to the MeanGSR measures between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-	X	X	X				X	X		X
Relax1	X	-	X	X		X		X	X	X	X
Stroop1	X	X	-	X		X	X	X	X	X	
Math1	X	X	X	-		X	X			X	
Read1					-						
BL2		X	X	X		-	X	X	X		X
Relax2			X	X		X	-	X	X	X	X
Stroop2	X	X	X			X	X	-		X	X
Math2	X	X	X			X	X		-	X	
Read2		X	X	X			X	X	X	-	X
Blood	X	X				X	X	X		X	-

Table 5.9: Student's t-test applied to the GSR number of events measures between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-		X	X	X					X	X
Relax1		-									
Stroop1	X		-			X				X	
Math1	X			-		X					
Read1	X				-	X	X				
BL2			X	X	X	-				X	X
Relax2					X		-			X	X
Stroop2								-			
Math2									-		
Read2	X		X			X	X			-	
Blood	X					X	X				-

Table 5.10: Student's t-test applied to the Corrugator Energy measures between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-		X	X	X		X	X	X		X
Relax1		-	X	X				X	X		X
Stroop1	X	X	-		X	X	X	X		X	
Math1	X	X		-	X	X	X			X	
Read1	X		X	X	-			X	X		X
BL2			X	X		-		X	X		X
Relax2	X		X	X			-	X	X		X
Stroop2	X	X	X		X	X	X	-		X	
Math2	X	X			X	X	X		-	X	
Read2			X	X				X	X	-	X
Blood	X	X			X	X	X			X	-

Table 5.11: Student's t-test applied to the Zigomatic Energy measures between each condition

-	BL1	Relax1	Stroop1	Math1	Read1	BL2	Relax2	Stroop2	Math2	Read2	Blood
BL1	-	X		X				X			
Relax1	X	-	X	X	X			X	X		
Stroop1		X	-			X	X			X	
Math1	X	X		-	X	X	X			X	
Read1		X		X	-			X			
BL2			X	X		-		X	X		
Relax2			X	X			-	X	X		
Stroop2	X	X			X	X	X	-		X	
Math2		X				X	X		-	X	
Read2			X	X				X	X	-	
Blood											-

Table 5.12: Student's t-test applied to the Heart Beat Rate measures between each condition

Chapter 6

Discussion

We have presented 3 researches concerning 3 different datasets, on which we have applied advanced signal processing techniques and Computational Intelligences (CI) algorithms to further analyse the extracted features. In each one of the presented researches we have applied machine learning techniques (concretely a classification step) to demonstrate the discrimination potential of EEG signals for different applications. The 3 different researches presented in this work are:

- Analysis of electrophysiological signals for biometric purposes (chapter 3).
- EEG differences in First Psychotic Episode (FPE) Patients (chapter 4).
- Markers of stress in the EEG signal (chapter 5).

As a reminder, the objectives stated in the introduction of this work (section 2) are listed below.

- Objective 1: Extract valuable information from EEG signals to build new applications. This generic objective summarises the main topic of this work. It is well known that valuable information can be extracted from EEG signals. For instance EEG is used as a diagnostic tool for several brain pathologies such as epilepsy and sleep disorders. EEG signals have also been widely used to build Brain Computer Interfaces (BCI) applications. In the case of this work, we have studied EEG signals for other applications that we consider quite novel.
- Objective 2: Study the potential of the EEG signals for biometric purposes. This objective includes a large data collection campaign and a study of different EEG features to find the ones most suited for a biometric system. As a note, we have also largely worked with ECG signals and to a lesser degree with EOG and EMG signals.
- Objective 3: Develop as unobtrusive a system as possible for EEG and ECG biometric, ideally using both modalities at the same time to increase the robustness.

- Objective 4: Study the potential use of EEG to discriminate between different populations of First Psychotic Episode (FPE) patients. These populations include FPE patients later diagnosed as schizophrenics, FPE patients that were not diagnosed as schizophrenics, schizophrenics after taking medication and finally a control group.
- Objective 5: Apply advanced signal processing techniques, such as complex networks and computational intelligence techniques to maximise the discrimination between the different FPE groups.
- Objective 6: Develop a protocol to induce different levels of stress and carry on the data recording campaign.
- Objective 7: Find stress markers in the EEG signals.

Regarding **Objective 1**, we have demonstrated that valuable information for 3 different novel applications can be extracted. EEG features have been found that allowed us to build a Biometric application, distinguish between FPE patients and matched controls and finally evaluate the stress level of subjects. These three applications are the core of this work. We consider that the generic Objective 1 has been successfully fulfilled.

Objective 2 has also been accomplished. We have undertaken a large data collection and have extracted several EEG features from which we have studied the more discriminative ones to be used as a biometric marker. The same can be concluded with the ECG signals that have also been studied for biometric purposes. From the first research presented in this thesis, a biometric system based on the ENOBIO sensor has been developed, which fulfils **Objective 3**.

With ENOBIO we can simultaneously record both EEG and ECG, using a total of 4 electrodes. In the first study we reached an EER equal to 3.4% for a system based on the EEG signal. In this case we were using a strict protocol in which the subject had to be seated, relax and keeping his/her eyes closed. In a second study, in which the protocol was not as strict as the precedent one, we reached an EER equal to 20.8% for EEG and equal to 2.1% for ECG. Although we observe a performance degradation in the EEG modality with respect to the first data set, by fusing the results of the EEG and ECG modalities, we were able to reach a TAR equal to 97.9% and a FAR equal to 0.82%. Actually, by tuning the decision function (with up to 12 parameters), we were able to reach a perfect performance (EER=0%). These very positive fusion results fulfils the second part of **Objective 3**.

We also performed a third study in which the subjects did not have to keep their eyes closed and were allowed to move freely (but remaining seated). In that case we developed an original movement artefact corrector algorithm. For this dataset we reached an EER equal to 25.6% for EEG and equal to 12.3% for ECG. Although the performance is lower in this case, it is important to take into account that the system is much less obtrusive now.

Taking into account that the ENOBIO sensor is wearable, and that the tendency of the electrophysiological sensors is to make them smaller and more and more wearable, such a system could be used in a continuous mode: if users wear such a device throughout the day, they could be authenticated in a continuos manner, without having to stop their tasks. For high security scenarios, such a system would be suitable and moreover, the user acceptance

should be high since such a system would not interfere with the tasks of the users. In other words, this system would be an always on (pervasive sensor) ambient intelligent device that would authenticate the user in a transparent manner.

Within this biometric research we have also worked with EMG signals. As a proof of concept, we developed a system in which, by recording the EMG of the forearm flexor (by placing two bipolar montages, one in each forearm), we were able to reach a CR equal to 95.8%. The subjects were asked to keystroke during the recording.

In the last part of this biometric research, we also propose a novel authentication method based on BCI. In this case, the user has to input a password in a computer by controlling the movement of a cursor in the screen with his EEG. As far as we know, such an approach has never been used before. In our case, we implemented such a system and tested it with a few subjects. Although there is a feeling of control over the system, the process is slow and not suitable for a biometric system, if the user acceptance is considered a priority. In any case, this system involves several biometric levels of security, making it very hard to spoof. First of all, the password is only known by the user. Besides that, the system is trained for each subject, and in principle it should not work for an impostor and finally, the user is the only one who knows which imaginary movements he/she has to perform. We believe that when BCI systems become more and more common, the potential for a biometric system based on this technology would be very interesting and well accepted. For instance we can think about a computer that would unlock for a particular subject only after the user has input his/her password by means of this BCI technology. Once unlocked, the computer would be personalised for this particular user. The same can apply to video games on which the BCI technologies are already finding its place, such as in the case of the Emotiv sensor.

The **Objective 4** has been accomplished in the second research presented in this thesis. We propose a system based on EEG able to find differences between different FPE populations. By analysing a 64 channel EEG dataset of SZ patients while having a FPE (pre) and after taking medication (post), patients suffering a FPE but that were not diagnosed as SZ (non SZ pre) and also a set of healthy controls (CON), we were able to reach CR rates as high as 100% between SZ pre and nSZ pre. We have performed several classification problems, and the lowest CR reached was 75% (CON vs SZ pre + SZ post).

Those high performances demonstrate the potential use of this system to diagnose SZ disease. The data analysis we have performed is quite innovative and consisted of extracting the Synchronisation Likelihood (SL) and Coherence (CO) feature for each pair of channels. With this information we were able to extract a connectivity graph, from which we extracted 3 features: Cluster Coefficient (CC), Path Length (PL) and Connectivity Index (KI). As we ended up with a very large number of features, we have implemented a GA for feature selection and finally classified them using FDA. This advance signal processing techniques fulfils the **Objective 5**. Indeed the positive results prove that the system developed herein has an interesting clinical potential.

We believe that such a system could be very useful as an extra source of information to help psychiatrists to diagnose SZ disease. As the EEG technique is unobtrusive, fast and cheap, it could be performed to patients before being diagnosed. Moreover this source of information would be completely objective. Based on his/her experience, the psychiatrist could also use

this information to fine tune his diagnosis and thus, be more precise with what kind of drug to prescribe. As far as we know, there is no such system described in the literature.

As a last word regarding this research, we are quite confident that such a system could be also applied to other mental diseases such as Alzheimer's Disease, Mild Cognitive Impairment, Depression, Bipolar Disorder, autism, attention deficit hyperactivity disorder, and so on. Of course, we should test this methodology with different datasets (containing EEG recordings from subjects suffering these mental conditions) to be able to confirm this affirmation. In any case, such an application would really be a breakthrough in mental disease diagnosis, and even more, in prevention and treatment. For instance we can imagine that if we are able to detect early signs of AD in the EEG of a subject (by applying a similar methodology using Machine Learning and the SL feature of the EEG), we could really improve her/his quality of life providing her/him with an early treatment of AD. A similar argument could hold for other diseases, and a very important point is that this methodology could really improve the prescription success, since it is well known that many patients are wrongly diagnosed and thus wrongly prescribed.

In the third and last research described in this thesis, we have looked for stress markers in the EEG signals. One of the main challenges of this work was to design a proper experimental protocol in which different levels of stress were induced to the participants, while recording their EEG and other physiological signals (facial EMG, ECG and GSR). In order to do so, we made the subjects perform several tasks such as relax, mathematical calculation, Stroop test and reading. After each tasks the participants had to fill a self-report questionnaire rating their level of several feelings. In the second part of the recording we introduced 3 actors to the participants as experts in non-verbal communication. These actors stayed in the recording room taking notes and staring at the subject. This was done to increase the social stress of the participants. Actually, this idea is inspired from the Trier Social Stress Test. Finally we faked a blood sample test to the subject. In fact, this task proved to be the most stressful after performing the data analysis. This protocol and its related recording campaign fulfils **Objective 6**. Indeed, some of the different tasks revealed statistically significant differences in the self-report questionnaires and in the features extracted from the peripheral sensors. These two independent sources of information were used as ground truth for our EEG signal analysis, from which we also found significant differences.

In a first stage we applied statistical data analysis by performing averages of the features over the subjects and we found interesting trends that agreed with the literature. From EEG we focus on symmetrical pairs of frontal channels (F3-F4 and F7-F8), and we extracted the Alpha Asymmetry and the Beta/Alpha ratio. We have found that the evolution of these features over the different tasks correlates with the stress level of each task, with the self-report questionnaires and with the other physiological signals. The most stressful event being the Fake Blood Sample task, and the lowest one being the Relax task.

We have also found that the presence of actors does not affect the level of stress recorded by the extracted features. One of the possible explanations of this finding is the habituation of the participants. They are probably already stressed in the first part of the experiment, when the actors are not present yet. This is because they are in a novel place, they do not know the researchers and they are attached to a lot of electrodes. During the second part of the experiment they are probably used to the novel environment, and thus, when the actors

are introduced, they are already habituated. Moreover, except for the Fake Blood Sample, the rest of the tasks are similar to the ones from the first part of the experiment.

The second and more ambitious part of this research was to work on a subject to subject basis by applying ML techniques. We have performed several classification problems, in every case using only 2 symmetrical EEG channels, referenced to CZ. The feature vectors have 3 components: Alpha Asymmetry chX-chY, Beta-Alpha ratio chX and Beta-Alpha ratio chY. As a summary we have reached a performance up to 88% for Baseline1 - Blood, 83% for Baseline2 - Stroop2 and also for Baseline2 - Blood 79% for Stroop2 - Blood and finally 75% Baseline1 and Stroop2.

These positive results demonstrate that using this methodology we could implement a system able to detect stress based on EEG, fulfilling **Objective 7**. Moreover, a focus on real time analysis has been taken in this work. Also, by using the wearable ENOBIO sensor, which is also wireless, this system could be easily used in many scenarios. An interesting application would be in VR Environments, in which the user, by wearing an EEG recording device, could have his/her stress level extracted in a real time manner. That could allow several options. The VR environment could be modified as a function of the stress level of the user. If the stress level recorded by the system is too high, the virtual scenario would change to a calmer environment so the stress level would decrease, and vice versa.

Such an application would be very useful for the treatment of stress for patients suffering from this disease. This idea is closely related to the concept of Neurofeedback. As our system allows a real time use, we could develop Neurofeedback applications for subjects in which they would learn to relax and control their stress levels. Another interesting application, also in a VR environment, and closely related with the Augmented Reality concept is the possibility to extract the stress level of users and show this information in their respective avatars, by means of colours or other types of representation. This would allow two avatars that meet in a VR environment to access information about the emotional/stress level of each other in an easy and visual way.

If we also add the authentication methodology implemented in the first research, we could also ensure the identities of the avatars in the VR environment. This would add an extra Augmented Reality information and would allow secure interactions between avatars in VR environment. As VR is a growing field of research and with time we will be using these types of platforms more and more, we believe that these types of applications are potentially very interesting. By wearing an EEG recording device (the ENOBIO sensor for instance), we can access different types of information (i.e. stress/emotion level and the user identity) at the same time, and use it in VR environments or in Neurofeedback applications.

As a final word, we want to stress that we believe that brain science will be very important and many new discoveries will be made during this century as physics has been revolutionised during the past 20th century. Each time we understand better how the brain works, but many things remain to be discovered. From a physical point of view, the brain is probably the most complex system in the (known) universe. Many approaches are possible to study the brain: from purely computational models to psychological and philosophical models, passing through biochemistry, biophysics, and medicine. Even quantum effects on the way the brain processes information have been proposed in some works, such as the one from Koch and Hepp [112]. Indeed, the brain can be seen from a microscopic point of view (molecular and atom level,

where quantum effects might be important), from a mesoscopic level, in which structures of few cm are considered (such as cortical neural networks) and finally from a macroscopic level in which the whole brain is seen as a unique system. There are many approaches to extract information from the brain, such as fMRI, PET and in the case of this work EEG. There are also novel techniques helpful to study the brain, such as brain stimulation (tDCS and TMS) and more invasive techniques such as deep brain stimulation. All these techniques combined are very helpful to discover the secrets of the brain functioning. It is also interesting to mention that one of the fastest growing fields in brain sciences are the so called BCI systems. Our work shares common similarities with those systems from a data analysis and classification point of view, and thus could also be applied to this field. Besides the development of these technologies, it is also very important to advance in the data processing techniques. We hope with this work to have contributed our bit to the development of this field.

Chapter 7

Final Conclusion

As explained in the previous section, each one of the objectives stated in the Introduction (section 2) has been accomplished. In this last section we will summarise the conclusions regarding each one of the initial objectives.

- Objective 1: Extract valuable information from EEG signals to build new applications (full objective 1 described in section 2).

  We have extracted different features from 3 different EEG data sets. In each research we have develop an application. These are a Biometrics system based on EEG (and ECG), a tool that discriminates between different populations of First Psychotic Episode subjects (and controls) and finally an application that extracts EEG features that correlates with different stress levels.

- Objective 2: Study the potential of the EEG signals for biometric purposes (full objective 2 described in section 2).

  We have found biometric potential in the EEG signals. We have also worked with ECG signals and actually we found more biometric potential in them, compared to EEG. As a proof of concept, we also worked with EOG and with EMG. Some biometric potential was also found on those signals.

- Objective 3: Develop as unobtrusive a system as possible for EEG and ECG biometric, ideally using both modalities at the same time to increase the robustness.

  For our biometric application we have used the ENOBIO sensor, which is wearable, wireless and only uses 4 channels. Using this sensor we were able to collect both EEG and ECG signals. By fusing both signals, we were able to reach very good classification rates, proving the potential for such a biometric system.

- Objective 4: Study the potential use of EEG to discriminate between different populations of First Psychotic Episode (FPE) patients (full objective 4 described in section 2).

  Taking into account the performances reached in our research, we conclude that EEG can be used to discriminate between different populations of FPE patients, and between FPE patients and controls.

- Objective 5: Apply advanced signal processing techniques, such as complex networks and computational intelligence techniques to maximise the discrimination between the different FPE groups.

  In order to maximise the performance of our system, we have applied complex networks (built using Synchronisation Likelihood and also Coherence) analysis and for the feature selection step, we have implemented a Genetic Algorithm that allowed us to reach quite significant performances.

- Objective 6: Develop a protocol to induce different levels of stress and carry on the data recording campaign.

  A protocol based on the Trier Social Stress Test in which the participants had to perform a different number of tasks alone and in front of actors (to induce social stress) was designed. After analysing the self-report questionnaires and the EMG, ECG and GSR measures, we can conclude that we successfully induced the desired levels of stress.

- Objective 7: Find stress markers in the EEG signals.

  An EEG analysis was performed and we found group tendencies among the participants by performing averages. In a second step, we applied machine learning techniques to work on a subject to subject basis, and we also found performances up to 88% while classifying the different stress-related tasks.

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Appendix A

List of Related Projects

This is the list of the main projects I have been involved and from where I was able to collect the data sets described and analysed in this thesis.

- HUMABIO: It stands for HUman Monitoring and Authentication using Biodynamic Indicators and behaviOral analysis. HUMABIO (FP6-2004-IST-4-026990) is a EC co-funded "Specific Targeted Research Project" (STREP) where new types of biometrics are combined with state of the art sensorial technologies in order to enhance security in a wide spectrum of applications like transportation safety and continuous authentication in safety critical environments like laboratories, airports or other buildings.

- ACTIBIO: It stands for unobtrusive authentication using ACTIvity related and soft BIOmetrics. ACTIBIO (also a EC co-funded "Specific Targeted Research Project" (STREP) under the FP7-2008-ICT) aims to research and develop a completely new concept in biometric authentication, i.e., the extraction of biometric signatures based on the response of the user to specific stimuli while performing specific work-related activities. The novelty of the approach lies in the fact that the measurements that will be used for authentication will correspond to the response of the person to specific events being however, fully unobtrusive and also fully integrated in an Ambient Intelligence infrastructure.

- SENSATION: It stands for Advanced Sensor Development for Attention, Stress, Vigilance and Sleep/Wakefulness Monitoring. SENSATION (also a EC co-funded IP under the FP6-IST) aims to explore a wide range of micro and nano sensor technologies, with the aim to achieve unobtrusive, cost-effective, real-time monitoring, detection and prediction of human physiological state in relation to wakefulness, fatigue and stress anytime, everywhere and for everybody.

- INTERSTRESS: It stands for Interreality in the Management and Treatment of Stress-Related Disorders. It is a European-funded project (Instrument: CP - ICT Grant Number FP7-247685). The INTERSTRESS project aims to design, develop and test an advanced ICT-based solution for the assessment and treatment of psychological stress. The work I have been involved was to look for stress markers in the EEG signals and also to develop a neurofeedback application for stress management/relaxation.

- TABULA RASA: It stands for Trusted Biometrics under Spoofing Attacks. Funded under 7th FWP (Seventh Framework Programme, Research area: ICT-2009.1.4 Trustworthy ICT). The TABULA RASA project address some of the issues of direct (spoofing) attacks to trusted biometric systems. This is an issue that needs to be addressed urgently because it has recently been shown that conventional biometric techniques, such as fingerprints and face, are vulnerable to direct (spoof) attacks.

- ENOBIO: This is an internal Starlab project where an EEG, ECG and EOG recording device was developed. This sensor is wireless, wearable and has 4 channels. After many years of hardware and software work and testing, the ENOBIO sensor has been successfully introduced in the market. I have been much involved in this project as a tester, application developer and support for the ENOBIO clients.

- SUENO: This is an CIDEM project (Spanish National funding agency) where the ENOBIO sensor has been benchmarked with other EEG recording devices used in Sleep Studies. A new configuration for the ENOBIO sensor was developed to allow its use in sleep recording. I was also involved in the EEG data analysis for sleep scoring.

- EYEDRIVE: This is an internal Starlab project where the use of Electro-oculagraphy was used to control a pointer in a screen.

- U-CONTROL: This is a CIDEM co-funded project where the use of EOG and EEG are explored to control several devices such as computers, wheelchairs, etc...

- PROYECTO ESQUIZOFRENIA: This is a Universitat de Barcelona (UB) project where EEG and ERP data was collected to First Psychotic Episode (FPE) patients.

Appendix B

Unobtrusive Biometric System Based on Electroencephalogram Analysis

In the following pages, a journal paper called "Unobtrusive Biometric System Based on Electroencephalogram Analysis" is presented. For complete reference please see Riera et al. [33].

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Research Article

Unobtrusive Biometric System Based on Electroencephalogram Analysis

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Features extracted from electroencephalogram (EEG) recordings have proved to be unique enough between subjects for biometric applications. We show here that biometry based on these recordings offers a novel way to robustly authenticate or identify subjects. In this paper, we present a rapid and unobtrusive authentication method that only uses 2 frontal electrodes referenced to another one placed at the ear lobe. Moreover, the system makes use of a multistage fusion architecture, which demonstrates to improve the system performance. The performance analysis of the system presented in this paper stems from an experiment with 51 subjects and 36 intruders, where an equal error rate (EER) of 3.4% is obtained, that is, true acceptance rate (TAR) of 96.6% and a false acceptance rate (FAR) of 3.4%. The obtained performance measures improve the results of similar systems presented in earlier work.

1. INTRODUCTION

The term "biometrics" can be defined as the emerging field of technology devoted to identification of individuals using biological traits, such as those based on retinal or iris scanning, fingerprints, or face recognition.

Biometrics is nowadays a big research playground, because a highly reliable biometric system results extremely interesting to all facilities where a minimum of security access is required. Identity fraud nowadays is one of the more common criminal activities and is associated with large costs and serious security issues. Several approaches have been applied in order to prevent these problems.

New types of biometrics, such as EEG and ECG, are based on physiological signals, rather than more traditional biological traits. This has its own advantages as we will see in the following paragraph.

An ideal biometric system should present the following characteristics: 100% reliability, user friendliness, fast operation, and low cost. The perfect biometric trait should have the following characteristics: very low intrasubject variability, very high intersubject variability, very high stability over time and universal. Typical biometric traits, such as fingerprint, voice, and retina, are not universal, and can be subject to physical damage (dry skin, scars, loss of voice, etc.). In fact, it is estimated that 2–3% of the population is missing the feature that is required for the authentication, or that the provided biometric sample is of poor quality. Furthermore, these systems are subject to attacks such as presenting a registered deceased person, dismembered body part or introduction of fake biometric samples.

Since every living and functional person has a recordable EEG signal, the EEG feature is universal. Moreover, brain damage is something that rarely occurs. Finally, it is very hard to fake an EEG signature or to attack an EEG biometric system.

The EEG is the electrical signal generated by the brain and recorded in the scalp of the subject. These signals are spontaneous because there are always currents in the scalp of living subjects. In other words, the brain is never at rest. Because everybody has different brain configurations (it is estimated that a human brain contains 10^{11} neurons and

10^{15} synapses), spontaneous EEG between subjects should be different; therefore a high intersubject variability is expected [11].

As it will be demonstrated with the results of our research, EEG presents a low intrasubject variability in the recording conditions that we defined: during one minute the subject should be relax and with his eyes closed. Furthermore, the system presented herein attains the improvement of the classification performance by combining a feature fusion with a classification fusion strategy. This kind of multistage fusion architecture has been presented in [22] as an advancement for biometry systems.

This paper describes a ready-to-use authentication biometric system based on EEG. This constitutes the first difference with already presented works [4, 5, 7–9]. The system presented herein undertakes subject authentication, whereas a biometric identification has been the target of those works. Moreover, they present some results on the employment of EEG as person identification cue [4, 5, 7–9], what herein becomes a stand-alone system.

A reduced number of electrodes have been already used in past works [4, 5, 7–9] in order to improve the system unobtrusiveness. This fact has been mimed in our system. There is however a differential trait. The two forehead electrodes are used in our system, while in other papers other electrodes configurations are used, for example, [5] uses electrode P4. Our long-term goal is the integration of the biometric system with the ENOBIO wireless sensory unit [23, 24]. ENOBIO uses dry electrodes, avoiding the usage of conductive gel and therefore improving the user friendliness. For achieving this goal employing electrodes in no hair areas becomes mandatory, a condition our system fulfils.

Lastly, performance evaluation is worth mentioning. Although we present an authentication system, we have conducted some identification experiments for the sake of comparison with already presented works [4, 5, 7–9]. The system presented herein shows a better performance by a larger number of test subjects. This question is further analyzed.

In the following sections, the used authentication methodology will be presented. Section 2 presents the EEG recording protocol and the data preprocessing. Section 3 deals with the features extracted from the EEG signal. Section 4 describes the authentication methodology, Section 5 the results; and finally conclusions are drawn in Section 6.

2. EEG RECORDING AND PREPROCESSING

For this study, an EEG database recorded at FORENAP, France, has been used. The database is composed of recordings of 51 subjects with 4 takes recorded on different days, and 36 subjects with only one take. All subjects were healthy adults between 20 and 45 years. The delay between the 1st and the 4th recording is 34 ± 74 days, whereby the medium-term stability of the system will be tested. The recording conditions were the same for all subjects: they were seated on an armchair in a dark room, with closed eyes and were asked neither to talk nor to move, and to relax. The recording duration was between 2 and 4 minutes. Only the 2 forehead electrodes (FP1 and FP2) were used for authentication; and an additional electrode that was placed in the left ear lobe was used as reference. The decision of using the frontal electrodes is due to projective integration with the ENOBIO system, which was presented in the former section. Indeed, the forehead is the most comfortable place where EEG can be measured.

The sampling rate for data acquisition was 256 Hz. A second-order pass band filter with cut frequencies 0.5 and 70 Hz was applied as the first preprocessing stage. A narrow notch filter at 50 Hz was additionally applied.

Once the filters were applied, the whole signal was cut in 4-second epochs. Artefacts were kept, in order to ensure that only one minute of EEG data will be used for testing the system.

3. FEATURES EXTRACTION

Among a large initial set of features (Higuchi fractal dimension, entropy, skewness, kurtosis, standard deviation, etc.), the five ones that show a higher discriminative power in the conducted preliminary works were used. These five different features were extracted from each 4-second epoch. These feature vectors are the ones that we will input in our classifiers.

We can distinguish between two major types of features: those extracted from a single channel (single channel features) and those that relate two different channels (the synchronicity features).

Autoregression (AR) and Fourier transform (FT) are examples of single channel features. They are calculated for each channel without taking into account the other one. These features have been used for EEG biometry in previous studies [1–10].

Mutual information (MI), coherence (CO), and cross-correlation (CC) are examples of two-channel features related to synchronicity [19–21]. They represent some joined characteristic of the two channels involved in the computation. This type of features is used for the first time in an EEG biometry system.

All the mentioned features are simultaneously computed in the biometry system presented herein. This is what we denote as the multifeature set. This set will be fused in subsequent stages of the system. The features are described in more detail in the following subsections.

3.1. Autoregression

The EEG signal for each channel is assumed to be the output of an autoregressive system driven by white noise. We use the Yule-Walker method, also known as the autocorrelation method, to fit a pth-order AR model to the windowed input signal, $X(t)$, by minimizing the forward prediction error in a least-square sense. This formulation leads to the Yule-Walker equations, which are solved by the Levinson-Durbin recursion. The AR model is represented by

$$X(t) = \sum_{i=1}^{p} a(i)X(t-i) + e(t). \quad (1)$$

In this model, the time series are estimated by a linear difference equation in the time domain, where a current sample of the signal $X(t)$ is a linear function of p previous samples plus an independent and identically distributed (i.i.d) white noise input $e(t)$. The average variance estimate of $e(t)$ is 0.75 computed for all the subjects. $a(i)$ are the autoregression coefficients. Preliminary results have shown the convenience of using an AR model with order 100.

3.1.1. Fourier transform

The well-known discrete Fourier transform (DFT), with expression

$$X(k) = \sum_{j=1}^{N} x(j) w_N^{(j-1)(k-1)}, \tag{2}$$

where

$$w_N = e^{(-2\pi i)/N} \tag{3}$$

is the Nth root of unity, is used herein to compute the DFT of each epoch. In our case, N is equal to 1024 (256 Hz∗4 seconds). We retain thence the frequency band from 1 to 40 Hz so that all EEG bands of interest are included: delta, theta, alpha, beta, and gamma.

3.1.2. Mutual information

In probability theory and information theory, the mutual information (MI), also known as *transinformation* [12, 21], of two random variables, is a quantity that measures the mutual dependence of the two variables. The most common unit of measurement of MI is the bit, when logarithms of base 2 are used in its computation. We tried different numbers of bits for coding the signal, choosing 4 as the optimal value for our classification purposes.

The MI has been defined as the difference between the sum of the entropies within two channels' time series and their mutual entropy.

3.1.3. Coherence

The purpose of the coherence measure is to uncover the correlation between two time series at different frequencies [19, 20]. The magnitude of the squared coherence estimate, which is a frequency function with values ranging from 0 to 1, quantizes how well x corresponds to y at each frequency.

The coherence $Cxy(f)$ is a function of the power spectral density (Pxx and Pyy) of x and y and the cross-power spectral density (Pxy) of x and y, as defined in the following expression:

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}. \tag{4}$$

In this case, the feature is represented by the set of points of the coherence function.

3.1.4. Cross-correlation

The well-known cross-correlation (CC) is a measure of the similarity of two signals, commonly used to find occurrences of a known signal in an unknown one. It is a function of the relative delay between the signals; it is sometimes called the sliding dot product, and has applications in pattern recognition and cryptanalysis.

We calculate three CCs for the two input signals:

(i) Ch1 with itself: ρX,
(ii) Ch2 with itself: ρY,
(iii) Ch1 with Ch2: ρXY.

The correlation ρXY between two random variables x and y with expected values μ_X and μ_Y and standard deviations σ_X and σ_Y is defined as

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E((X-\mu_X)(Y-\mu_Y))}{\sigma_X \sigma_Y}, \tag{5}$$

where

(i) $E()$ is the expectation operator,
(ii) cov() is the covariance operator.

In this case, the features are represented by each point of the three calculated cross-correlations. This feature is referred to as CC in the following section.

4. AUTHENTICATION METHODOLOGY

The work presented herein is based on the classical Fisher's discriminant analysis (DA). DA seeks a number of projection directions that are efficient for discrimination, that is, separation in classes.

It is an exploratory method of data evaluation performed as a two-stage process. First the total variance/covariance matrix for all variables, and the intraclass variance/covariance matrix are taken into account in the procedure. A projection matrix is computed that minimizes the variance within classes while maximizing the variance between these classes. Formally, we seek to maximize the following expression:

$$J(W) = \frac{|W^t S_B W|}{|W^t S_W W|}, \tag{6}$$

where

(i) W is the projection matrix,
(ii) S_B is between-classes scatter matrix,
(iii) S_W is within-class scatter matrix.

For an n-class problem, the DA involves $n-1$ discriminant functions (DFs). Thus a projection from a d-dimensional space, where d is the length of the feature vector to be classified, into an $(n-1)$-dimensional space, where $d \geq n$, is achieved. In our algorithm, we work with 4 different DFs:

(i) linear: fits a multivariate normal density to each group, with a pooled estimate of the covariance;
(ii) diagonal linear: same as "linear," except that the covariance matrices are assumed to be diagonal;

(iii) quadratic: fits a multivariate normal density with covariance estimates stratified by group;
(iv) diagonal quadratic: same as "quadratic," except that the covariance matrices are assumed to be diagonal.

The interested reader can find more information about DA in [13].

Taking into account the 4 DFs, the 2 channels, the 2 single channel features, and 3 synchronicity features, we have a total of 28 different classifiers. Here, we mean by classifier, each of the 28 possible combinations of feature, DF, and channel.

We use an approach that we denote as "personal classifier," which is explained herein, for the identity authentication case: the 5 best classifiers, that is, the ones with more discriminative power, are used for each subject. When a test subject claims to be, for example, subject 1, the 5 best classifiers for subject 1 are used to do the classification. In order to select the 5 best classifiers for the 51 subjects with 4 EEG takes, we proceed as follows. We use the 3 firsts takes of the 51 subjects for training each classifier, and the 4th take of a given subject is used for testing it. We repeat this process making all possible combinations (using one take for testing and the others for training). Each time we do this process, we obtain a classification rate (CR): number of feature vectors correctly classified over the total number of feature vectors. The total number of feature vectors is around 45, depending on the duration of the take. Once this process is repeated for all 28 classifiers, we compute a score measure on them, which can be defined as

$$\text{score} = \frac{\text{average(CR)}}{\text{standard deviation(CR)}}. \tag{7}$$

The 5 classifiers with higher scores out of the 28 possible classifiers are the selected ones. We repeat this process for the 51 subjects.

Once we have the 5 best classifiers for all 51 subjects, we can then implement and test our final application. We now proceed in a similar way, but we only use in each test the first or the second minute of a given take, that is, we input in each one of the 5 best classifiers 15 feature vectors. Each classifier outputs a posterior matrix (Table 1). In order to fuse the results of the 5 classifiers, we vertically concatenate the 5 obtained posterior matrices and take the column average. The resulting vector is the one we will use to take the authentication decision (in fact it is a probability density function (PDF); see Figures 1(a) and 1(b), where the 1st element is the probability that the single minute test data comes from subject 1 and the 2nd element is the probability that the single minute test data comes from subject 2, and so forth.

The last step in our algorithm takes into consideration a decision rule over the averaged PDF. We use two different thresholds. The first one is applied on the probability of the claimed subject. The second threshold is applied on the signal-to-noise ratio (SNR) of the PDF, which we define as

$$\text{SNR}_i = \frac{P^2(x_i / x_i \in C^i)}{\sum_{j \neq i} P^2(x_j / x_j \in C^j)}, \tag{8}$$

where $P(x_i / x_i \in C^i)$ is the probability that the single minute test data comes from.

5. RESULTS

In the first part of this section, we provide the results for our authentication system. Then, for the sake of comparison with related works, which only deal with identification, we also provide the results of a simplified version of the "personal classifier" approach. This approach works as an identification system, that is, the claimed identity of the user is not taken into consideration as an input.

5.1. Authentication system results

Three different tests have been undertaken on our EEG-based biometric system in order to evaluate its classification performance:

(i) legal test: a subject belonging to thedatabase claims his real identity,
(ii) impostor test: a subject belonging to thedatabase claims the identity of another subject belonging to the database,
(iii) intruder test: a subject who does not belong to the database claims the identity of a subject belonging to the database.

We have used the data of the 51 subjects with 4 takes in the database for the legal and the impostor tests. For the intruder test, the 36 subjects with 1 take have been applied to the system. An easy way to visually represent the system performance is the classification matrices (Figures 2(a) and 2(b)). These are defined by entries c_{ij}, which denote the number of test feature vectors from subject i classified as subject j.

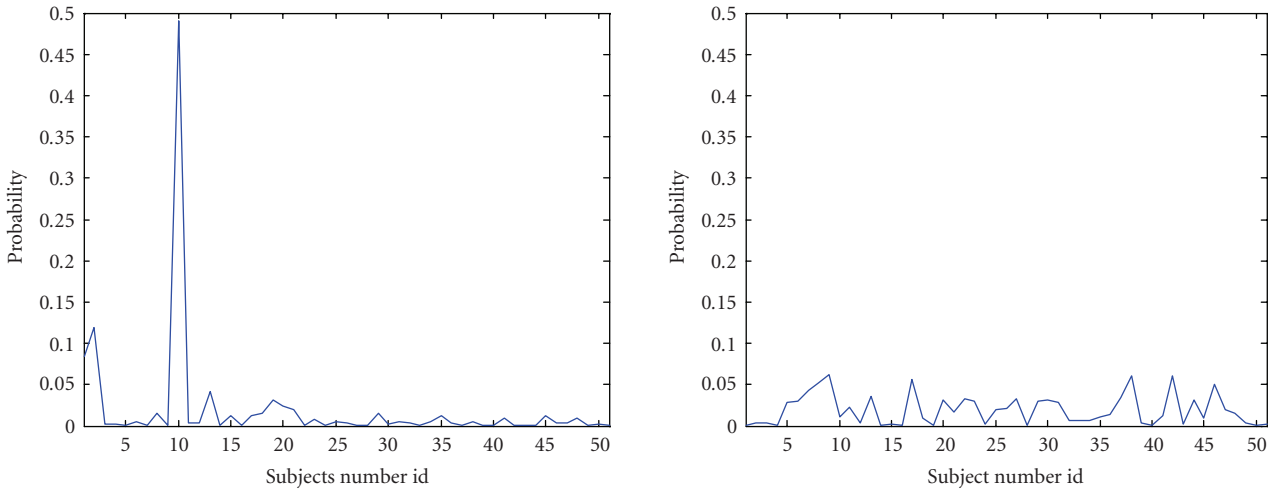
Taking into account that we have 4 test takes, and that we use both the first and the second minutes for testing, we have $4*2*51 = 408$ legal situation trials (N_{leg}). In the case of the impostor situation, we have also 4 takes, we also use the first and the second minutes of each take, we have 51 impostors that are claimed to be the other 50 subjects from the database. Therefore, we have $4*2*51*50 = 20{,}400$ impostor situation trials (N_{imp}). For the intruder situation, we have 1 test take from which we only use the first minute, so we have $1*1*36*51 = 1{,}836$ intruder situation trials (N_{int}). We use the true acceptance rate (TAR) and the false acceptance rate (FAR) as performance measures of our system. They are defined for each individual subject in each trial situation as following:

$$\begin{aligned} \text{TAR}_i &= \frac{c_{ii}}{\sum_{j=1}^{N} c_{ij}}, \\ \text{FAR}_i &= \frac{\sum_{j=1}^{N} c_{ji}}{\sum_{j=1}^{N} \sum_{k=1}^{N} c_{jk}} \quad \forall j \neq i, \end{aligned} \tag{9}$$

where c_{ij} denote the classification matrix entries as defined in the previous section, N the number of subjects for each trial situation, either legal/impostor ($N = 51$) or intruders ($N = 36$). It is worth mentioning that for this second case, no TAR_i can be defined.

Table 1: Posterior matrix of the 15 FT feature vectors extracted from one minute EEG recording of subject 1. Each row represents the probabilities assigned to each class for each feature vector. We see that the subject is well classified as being subject 1 (refer to the last row). Notice that this posterior matrix represents a 9-class problem and our work is done for a 51 class problem.

Classified as	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9
Test 1	0.46	0.28	0	0	0.23	0	0	0	0
Test 2	0.40	0.24	0	0	0.11	0	0	0	0.23
Test 3	0.99	0	0	0	0	0	0	0	0
Test 4	0.99	0	0	0	0	0	0	0	0
Test 5	0.99	0	0	0	0	0	0	0	0
Test 6	0.91	0.01	0.04	0	0	0	0	0.04	0
Test 7	0.99	0	0	0	0	0	0	0	0
Test 8	0.99	0.01	0	0	0	0	0	0	0
Test 9	0.96	0	0.02	0	0	0	0	0	0
Test 10	0.99	0	0	0	0	0	0	0	0
Test 11	0.16	0.04	0	0	0	0	0.25	0	0.53
Test 12	0.53	0.35	0	0	0	0	0	0	0.11
Test 13	0.92	0.07	0	0	0	0	0	0	0.01
Test 14	0.99	0	0	0	0	0	0	0	0
Test 15	1	0	0	0	0	0	0	0	0
Average	0.81	0.07	0.01	0	0.03	0	0.02	0	0.06



(a) (b)

Figure 1: PDF for normal situation for subject 10 (a) and for intruder situation (b). In (a), notice that if a probability threshold is set to 0.15, subject 10 will be authenticate only if he claims to be subject 10. In (a), the intruder would not be authenticated in any case.

The general system TAR is computed as the average over all subjects:

$$\mathrm{TAR} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{TAR}_i. \tag{10}$$

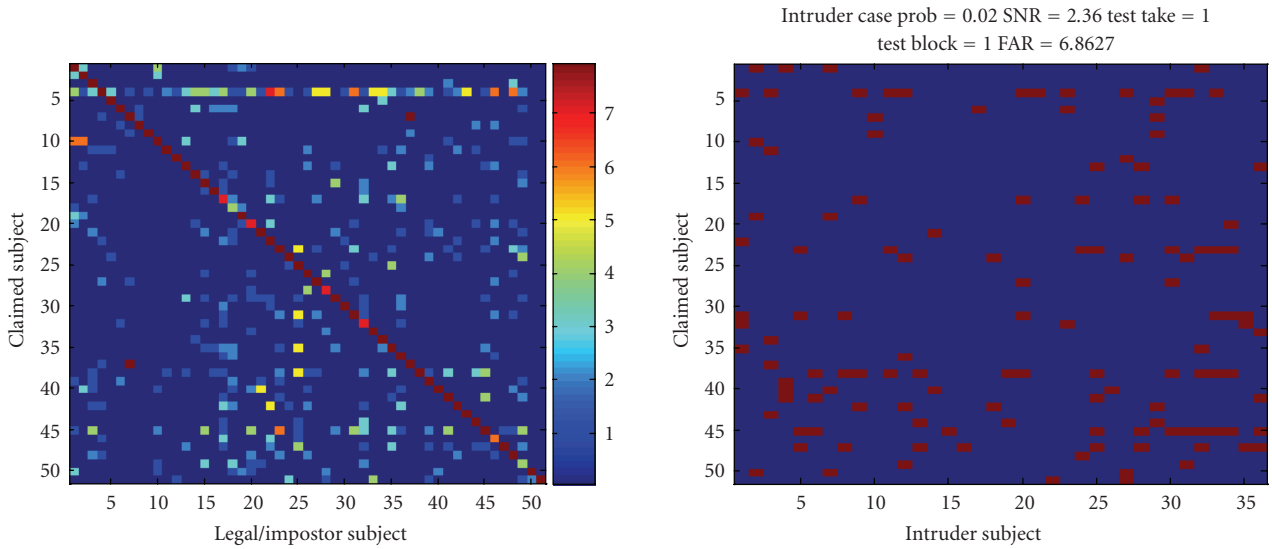
The general FAR can be computed in an analogous manner for the two different groups of impostors (N = 51) and intruders (N= 36).

As it can be observed, we get two different FAR measures for the impostor and the intruder cases. These two measures are weighted averaged in order to obtain a unique FAR measure as follows:

$$\mathrm{FAR} = \frac{N_{\mathrm{imp}}}{N_{\mathrm{imp}} + N_{\mathrm{int}}}\mathrm{FAR}_{\mathrm{imp}} + \frac{N_{\mathrm{int}}}{N_{\mathrm{imp}} + N_{\mathrm{int}}}\mathrm{FAR}_{\mathrm{int}}, \tag{11}$$

where $\mathrm{FAR}_{\mathrm{imp}}$ is the average of FAR_i over the 51 impostors, $\mathrm{FAR}_{\mathrm{int}}$ is the average of FAR_i over the 36 intruder

We finally obtain an equal error rate (EER) measure that equals 3.4%. This value is achieved for a probability threshold equal to 0.02 and an SNR threshold equal to 2.36. In Figure 3, we can see the behavior of TAR and FAR for



(a) (b)

Figure 2: Classification matrices. The subjects in the x axes claim to be all the subjects from the database. In (a), we see that the diagonal is almost full. These are the cases where a subject truthfully claims to be himself. The off-diagonal elements represent the impostor cases. Note that we are showing the results of the 8 possible test trials together. In (b), the intruder cases are shown. Only one trial was made per intruder.

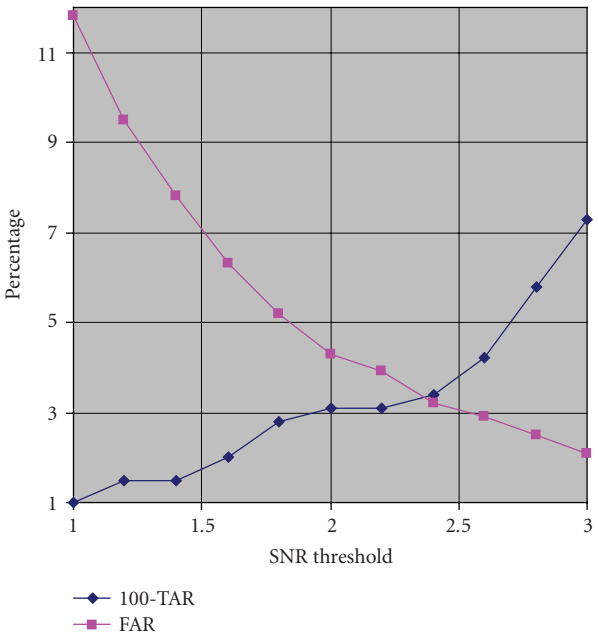


Figure 3: Behavior of TAR and FAR for a fixed probability threshold of 0.02 and modifying the SNR threshold for the "authentication mode." The intersection of the two curves is the EER.

different SNR thresholds (with probablitiy thresholds fixed to 0.02).

Depending on the security level, different thresholds can be applied in order to make the system more inaccessible for intruders, but this would also increase the number of legal subjects that are not authenticated as shown in Figure 3.

5.2. Comparison in an identification task

It is easy to slightly modify the described system to work in an identification mode. Indeed, this "identification mode" is a simplification of the authentication one. Rather than using personalized classifiers for each subject, what we do now is to use the same 16 classifiers for all the subjects. Those classifiers are the ones that have more discriminative power among all subjects. They are given in the Table 2.

It is worth pointing out that a trivial classifier would yield a CR equal to 0.0196 (i.e., 1/number of classes, which in our case is 51). Moreover, the results obtained after fusing the different classifiers significantly improve the performance of the identification system as depicted in Figure 4. This improvement of performance is also achieved in the "authentication mode."

Figure 4 shows the behavior of the TAR and FAR for our system in "identification mode." We can see that 3 different operating points are marked. Those are the values we will use for the comparison.

Table 2 shows several results from other works along with the results of our current work, in 3 different operating points.

6. DISCUSSION AND CONCLUSIONS

An authentication biometric system based on EEG, using 2 frontal electrodes plus 1 reference placed at the left ear lobe, is described in this paper. The tested subject has to sit, close her eyes, and relax during one minute of EEG recording. The only inputs to the system are the one-minute EEG recording and the claimed identity of the subject. The output is a binary decision: authenticated or not. This authentication system

Table 2: Classification rate for the sixteen best classifiers used for all subjects in the "identification mode."

Feat	D.Fun	Ch	CR	Feat	D.Fun	Ch	CR
ff	lin	2	0.42	ar	lin	2	0.34
ff	lin	1	0.41	ar	lin	1	0.29
ff	quad	1	0.40	cc	lin	—	0.31
ff	quad	2	0.39	co	lin	—	0.24
ff	diaglin	2	0.36	mi	lin	—	0.24
ff	diagquad	2	0.36	cc	quad	—	0.23
ff	diaglin	1	0.35	co	quad	—	0.21
ff	diagquad	1	0.35	mi	quad	—	0.19

Table 3: EEG identification results extracted from literature and from our present work.

Study	No. of subjects	No. of leads	Performance (classification rate)	TAR	FAR
Poulos et al. (1999) [7]	4 (+75 intruders)	2	95%	65%	16.9%
Poulos et al. (2001) [8]	4 (+75 intruders)	2	80–100%	92.9%	13.6%
Poulos et al. (2002) [9]	4 (+75 intruders)	2	76–88%	79%	19.8%
Paranjape et al. (2001) [5]	40	2	79–85%	-not available-	-not available-
Mohammadi et al. (2006) [4]	10	2 or 3	80–97% single channel 85–100% multi channel	-not available-	-not available-
Present paper (op1)	51 (+36 intruders)	3	98.1%	99%	14.3%
Present paper (op2)	51 (+36 intruders)	3	95.1%	94.5%	5.5%(EER)
Present paper (op3)	51 (+36 intruders)	3	87.5%	88.7%	2%

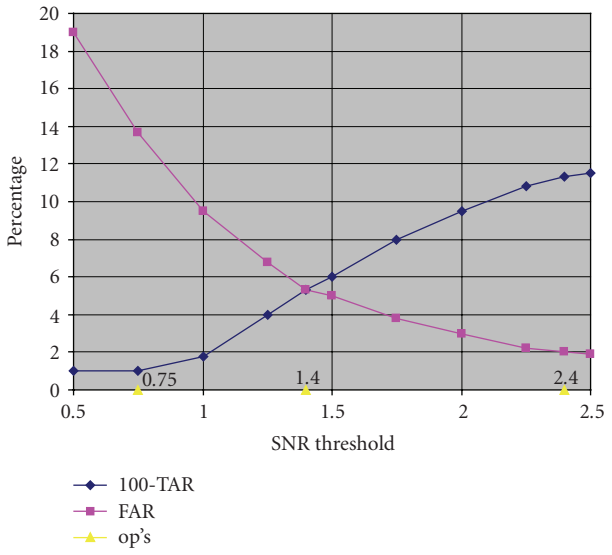


Figure 4: Behavior of TAR and FAR for a fixed probability threshold of 0.02 and modifying the SNR threshold for the "identification mode." The intersection of the two curves is the EER. Three operating points (up) have been chosen at different SNR thresholds (0.75, 1.4, and 2.4)

demonstrates to outperform the same system in "identification mode" (EER = 3.4% versus EER = 5.5%). The "identification mode" is adopted only to compare with precedent studies [4, 5, 7–9], since they deal only with identification.

The results of our system in "identification mode" outperform precedent works even though a larger database has been used to test our system. Intruders have also been used to test the intruder detection.

We consider that the more innovative point in this study is the use of several features and the way they are personalized and fused for each subject. We focus on extracting the maximum possible information from the test takes, taking care of the unobtrusiveness of the system: with only one minute of recording, using only the two forehead channels, we obtain 28 different classifiers, from which the 5 ones with more discriminative power for each subject are selected. In order to have an even more reliable system, a multimodal approach would probably increase the performance considerably. We are investigating the possibility of applying an electrocardiogram (ECG)-based biometry simultaneously to the EEG [14–18]. Combining EEG and ECG biometric modalities seems to be very promising and will be discussed in a follow-up paper.

Another possible application that we are researching is whether the emotional state (stress, sleepiness, alcohol, or drug intake) can be extracted from EEG and ECG. In this case, besides the authentication of the subject, we could undertake his initial state validation. This would be a very interesting application for workers of critical or dangerous environments.

Finally, the usage of less than one minute of EEG data recording is being studied in order to make the system less obtrusive. This condition will be improved as well with the ENOBIO sensory integration.

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Appendix C

Multimodal Physiological Biometric Authentication

This enclosed work that follows was published as a chapter in a book called "Biometrics: Theory, Methods, and Applications" published by John Wiley and Sons, Inc. in 2009. For complete reference please see Riera et al. [34].

1 Multimodal Physiological Biometrics Authentication

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1.1 INTRODUCTION

The term biometry is derived from the Greek words 'bios' (life) and 'metron' (measure). In the broader sense, biometry can be defined as the measurement of body characteristics. With this non-technological meaning, this term has been used in medicine, biology, agriculture and pharmacy. For example, in biology, biometry is a branch that studies biological phenomena and observations by means of statistical analysis.

However, the rise of new technologies since the second half of the 20th century to measure and evaluate physical or behavioural characteristics of living organisms automatically has given the word a second meaning. In the present study, the term biometrics refers to the following definition [33]:

> The term biometry refers to automated methods and techniques that analyze human characteristics in order to recognise a person, or distinguish this person from another, based on a physiological or behavioural characteristic.

Biometry, however, has also acquired another meaning in the last decades, focused on the characteristic to be measured rather than the technique or methodology used [33]:

A biometric is a unique, measurable characteristic or trait of a human being for automatically recognising or verifying identity.

These definitions contain several important concepts that are critical to biometry:

Unique: In order for something to be unique, it has to be the only existing one of its type, have no like or equal, be different from all others. When trying to identify an individual with certainty, it is absolutely essential to find something that is unique to that person.

Measurable: In order for recognition to be reliable, the characteristic being used must be relatively static and easily quantifiable. Traits that change significantly with time, age, environment conditions or other variables are of course not suitable for biometrics.

Characteristic or trait: Measurable physical or personal behavioural pattern used to recognise a human being. Currently, identity is often confirmed by something a person has, such as a card or token, or something the person knows, such as a password or a personal identification number. Biometrics involves something a person is or does. These types of characteristics or traits are intrinsic to a person, and can be approximately divided into physiological and behavioural. Physiological characteristics refer to what the person is, or, in other words, they measure physical parameters of a certain part of the body. Some examples are fingerprints, that use skin ridges, face recognition, using the shape and relative positions of face elements, retina scanning, etc. Behavioural characteristics are related to what a person does, or how the person uses the body. Voice or gait recognition, and keystroke dynamics, are good examples of this group.

Automatic: In order for something to be automatic it must work by itself, without direct human intervention. For a biometric technology to be considered automatic, it must recognize or verify a human characteristic in a reasonable time and without a high level of human involvement.

Recognition: To recognize someone is to identify them as someone who is known, or to distinguish someone because you have seen, heard or experienced them before (to 'know again'). A person cannot recognise someone who is completely unknown to them. A computer system can be designed and trained to recognise a person based on a biometric characteristic, comparing a biometric presented by a person against biometric samples stored in a database If the presented biometric matches a sample on the file, the system then recognises the person.

Verification: To verify something is to confirm its truth or establish its correctness. In the field of biometrics, verification is the act of proving the claim made by a person

about their identity. A computer system can be designed and trained to compare a biometrics presented by a person against a stored sample previously provided by that person and identified as such. If the two samples match, the system confirms or authenticates the individual as the owner of the biometrics on file.

Identity: Identity is the answer to the question about who a person is, or the qualities of a person or group which make them different from others, i.e., being a specific person. Identity can be understood either as the distinct personality of an individual regarded as a persistent entity, or as the individual characteristics by which this person is recognised or known. Identification is the process of associating or linking specific data with a particular person.

A biometric system is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database. Depending on the application context, a biometric system may operate either in authentication mode or identification mode:

- **Authentication** (Greek: $\alpha\upsilon\theta\epsilon\nu\tau\iota\kappa\phi\varsigma$, from 'authentes'='author') is the act of proving the claim made by a person about their identity. In other words, the authentication of a person consists in verifying the identity they declare. In the authentication mode, the system validates a person's identity by comparing the captured biometric data with her own biometric template(s) stored system database. In such a system, an individual who desires to be recognised claims an identity, usually via a PIN (Personal Identification Number), a user name, a smart card, etc., and the system conducts a one-to one comparison to determine whether the claim is true or not (e.g., 'Does this biometric data belong to X?'). Identity verification is typically used for positive recognition, where the aim is to prevent multiple people from using the same identity. Authentication is also commonly referred to as verification.
- **Identification** (Latin: idem-facere, 'to make the same') is the act of recognizing a person without any previous claim or declaration about their identity. In other words, the identification of a person consists in recognizing them, that person being aware or not of this recognition task being performed. In the identification mode, the system recognises an individual by searching the templates of all the users in the database for a match. Therefore, the system conducts a one-to-many comparison to establish an individual's identity (or fails if the subject is not enrolled in the system database) without the subject having to claim an identity (e.g., 'Whose biometric data is this?'). Identification is a critical component in negative recognition applications where the system establishes whether the person is who she (implicitly or explicitly) denies to be. The purpose of negative recognition is to prevent a single person from using multiple identities. Identification may also be used in positive recognition for convenience (the user is not required to claim an identity). While traditional

methods of personal recognition such as passwords, PINs, keys, and tokens may work for positive recognition, negative recognition can only be established through biometrics.

In our paper we will describe a system that works on authentication mode, although it is quite straight forward to modify it to work on identification mode [25].

The increasing interest in biometry research is due to the increasing need for highly reliable security systems in sensitive facilities. From defense buildings to amusement parks, a system able to identify subjects in order to decide if they are allowed to pass or not would be very well accepted. This is because identity fraud nowadays is one of the more common criminal activities and is associated with large costs and serious security issues. Several approaches have been applied in order to prevent these problems. Several biometric modalities are already being used in the market: voice recognition, face recognition and fingerprint recognition are among the more common modalities nowadays. But other types of biometrics are being studied nowadays as well: ADN analysis, keystroke, gait, pa print, ear shape, hand geometry, vein patterns, iris, retina and written signature.

New types of Biometrics, such as electroencephalography (EEG) and electrocardiography (ECG), are based on physiological signals, rather than more traditional biological traits. These have their own advantages as we will see in the following paragraphs.

An ideal biometric system should present the following characteristics: 100% reliability, user friendliness, fast operation and low cost. The perfect biometric trait should have the following characteristics: very low intra subject variability, very high inter subject variability, very high stability over time and universal. Typical biometric traits, such as fingerprint, voice and retina, are not universality, and can be subject to physical damage (dry skin, scars, loss of voice, ...). In fact, it is estimated that 2-3% of the population is missing the feature that is required for authentication, or that the provided biometric sample is of poor quality. Furthermore, these systems are subject to attacks such as presenting a registered deceased person, dismembered body part or introduction of fake biometric samples. Since every living and functional person has a recordable EEG/ECG signal, the EEG/ECG feature is universal. Moreover brain or heart damage is something that rarely occurs. Finally it is very hard to fake an EEG/ECG signature or to attack an EEG/ECG biometric system.

EEG is the electrical signal generated by the brain and recorded in the scalp of the subject. These signals are spontaneous because there are always currents in the scalp of living subjects. In other words, the brain is never at rest. Because everybody has different brain configurations (it is estimated that a human brain contains 10^{11} neurons and 10^{15} synapses), spontaneous EEG between subjects should be different; therefore a high inter-subject variability is expected [11].

A similar argument can be applied to ECG. This signal describes the electrical activity of the heart, and it is related to the impulses that travel through it. It provides information about the heart rate, rhythm and morphology. As these characteristics are very subject-dependent, a high inter-subject variability is also expected. This has been shown in previous works [14, 15, 16, 17 ,18].

As will be demonstrated using the results of our research, EEG and ECG present a low intra-subject variability in the recording conditions we defined: during one minute the subject should be relaxed and with their eyes closed. Furthermore the system presented herein attains an improvement of classification performance by combining feature fusion, classification fusion and multimodal biometric fusion strategies. This kind of multi-stage fusion architecture has been presented in [22] as an advancement for biometry systems.This paper describes a ready-to-use authentication biometric system based on EEG and ECG. This constitutes the first difference with already presented works [4, 5, 7, 8, 9, 14, 15, 16, 17, 18, 25]. The system presented herein undertakes subject authentication, whereas a biometric identification has been the target of those works. Moreover they present some results on the employment of EEG and ECG as a person identification cue, what herein becomes a stand-alone system.

A reduced number of electrodes have been already used in past works [4, 5, 7, 8, 9, 25] in order to reduce system obtrusiveness. This feature has been implemented in our system. There is however a differential trait. The two forehead electrodes are used in our system, while in other papers other electrodes configurations are used, e.g. [5] uses electrode P4. Our long-term goal is the integration of the biometric system with the ENOBIO wire-less sensory unit [23, 24, 32]. ENOBIO can use dry electrodes, avoiding the usage of conductive gel and therefore improving the user friendliness. In order to achieve this goal employing electrodes on hairless areas becomes mandatory, a condition our system fulfills.

In the following sections, our authentication methodology will be presented. Section 1.2 explains the experimental protocol which is common for EEG and ECG recording. Section 1.3 deals with the EEG extracted features and the authentication algorithms while section 1.4 is dedicated to the ECG features and algorithms. For these two sections, the performances are also individually given. Section 1.5 explains the fusion process carried out to achieve higher performance. Finally, conclusions are drawn in section 1.6 while section 1.7 provides a summary of the chapter.

1.2 EXPERIMENTAL PROTOCOL

A database of 40 healthy subjects (30 males and 10 females, aged from 21 to 62 years) has been collected in order to evaluate the performance of our system. An in-

formed consent along with a health questionnaire was signed and filled by all subjects.

The EEG/ECG recording device is ENOBIO, a product developed at STARLAB BARCELONA SL. It is wireless and implements 4 channel (plus the common mode) device with active electrodes. It is therefore quite unobtrusive, fast and easy to place. Even thought ENOBIO can work on dry mode, in this study conductive gel has been used. In Figure 1.1, we can see the ENOBIO sensor integrated in a cap and wear by a subject.

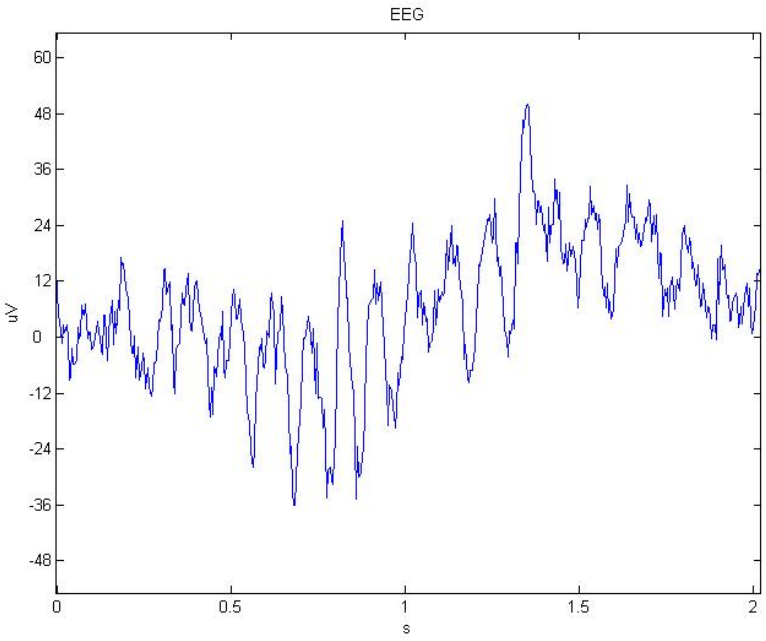
Fig. 1.1 ENOBIO EEG recording sample of 2 seconds with no pre-processing. The alpha wave (10 Hz characteristic EEG wave) can be seen.

In Figure 1.2, a sample of EEG recorded with ENOBIO is shown. An ECG sample data is also shown in Figure 1.3. Notice that the EEG amplitude is typically about 60 microvolts while ECG amplitude is typically about 1000 microvolts, therefore it is always more complicated to obtain a good EEG recording than an ECG, as the signal to noise ratio is easier to maximize with a stronger signal. No pre-processing has been done on these sample signals.

The electrode placement is as follows:

- two on the forehead (FP1 and FP2) for EEG recording

Fig. 1.2 ENOBIO EEG recording sample of 2 seconds with no pre-processing. The alpha wave (10 Hz characteristic EEG wave) can be seen.

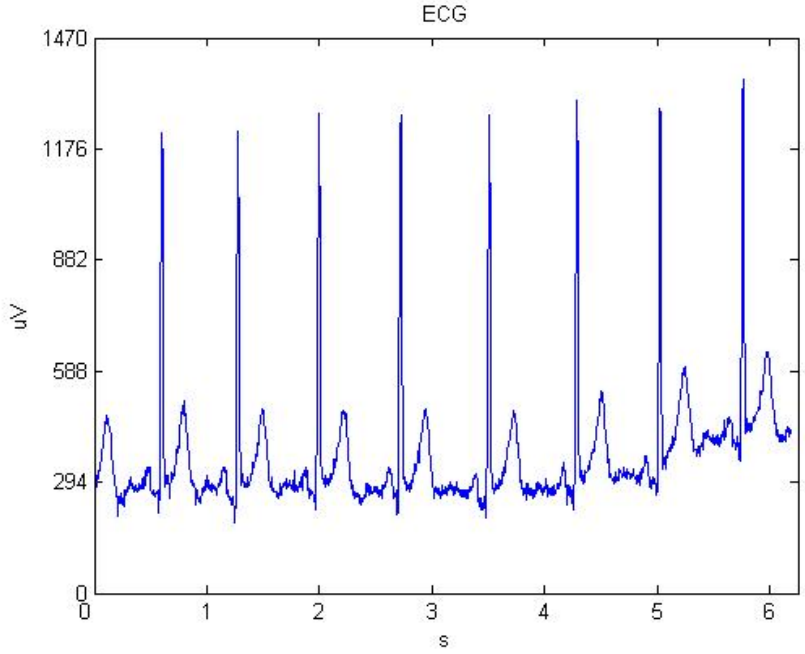


- one on the left wrist for ECG recording
- one on the right earlobe as reference
- one on the left earlobe as the hardware common mode

At this time, conductive gel is used, but in the future ENOBIO will work without gel, using carbon nanotube technology. Some tests have been done using this new electrodes with very positive results [23, 24], but at the moment some biocompatibility studies are being planned in order to approve their commercial use.

The recordings are carried out in a ca environment. The subjects are asked to sit in a comfortable armchair, to relax, be quiet and close their eyes. Then three 3-minute takes are recorded to 32 subjects and four 3-minutes takes are recorded to the 8 subjects, preferably on different days, or at least at different moments of the day. The 32 subject set are used as reference subject in the classification stage and the 8 subjects are the ones that are enrolled into the systems. Then several 1-minute takes are recorded afterwards to these enrolled subjects, in order to use them as authentication tests. Both the enrolment takes and the authentication takes are recorded

Fig. 1.3 ENOBIO ECG recording sample of approximately 6 seconds with no pre-processing.



under the same conditions.

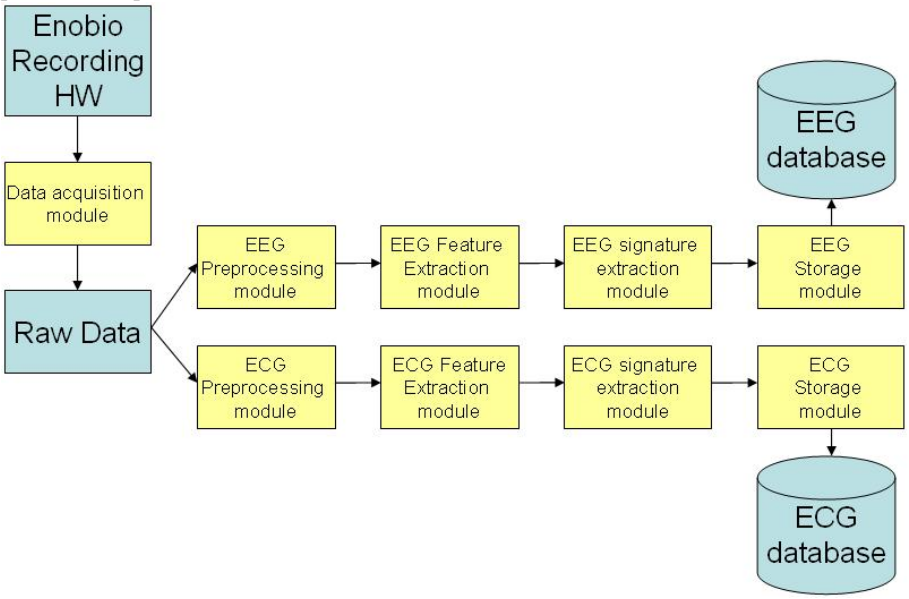
1.3 AUTHENTICATION ALGORITHM BASED ON EEG

We begin this section with two flowcharts that describe the whole application, in order to clarify all the concepts involved. As with all the other biometric modalities, our system works in two steps: enrolment and authentication. This means that for our system to authenticate a subject, this subject needs first of all to enroll into the system. In other words, their biometric signature has to be extracted and stored in order to retrieve it during the authentication process. Then the sample extracted during the authentication process is compared with the one that was extracted during the enrolment. If they are similar enough, then they will be authenticated.

1.3.1 EEG pre-preprocessing

First of all, a pre-processing step is carried on the two EEG channels. They are both referenced to the right earlobe channel in order to cancel the common interference that can appear in all the channels. This is a common practice in EEG recordings.

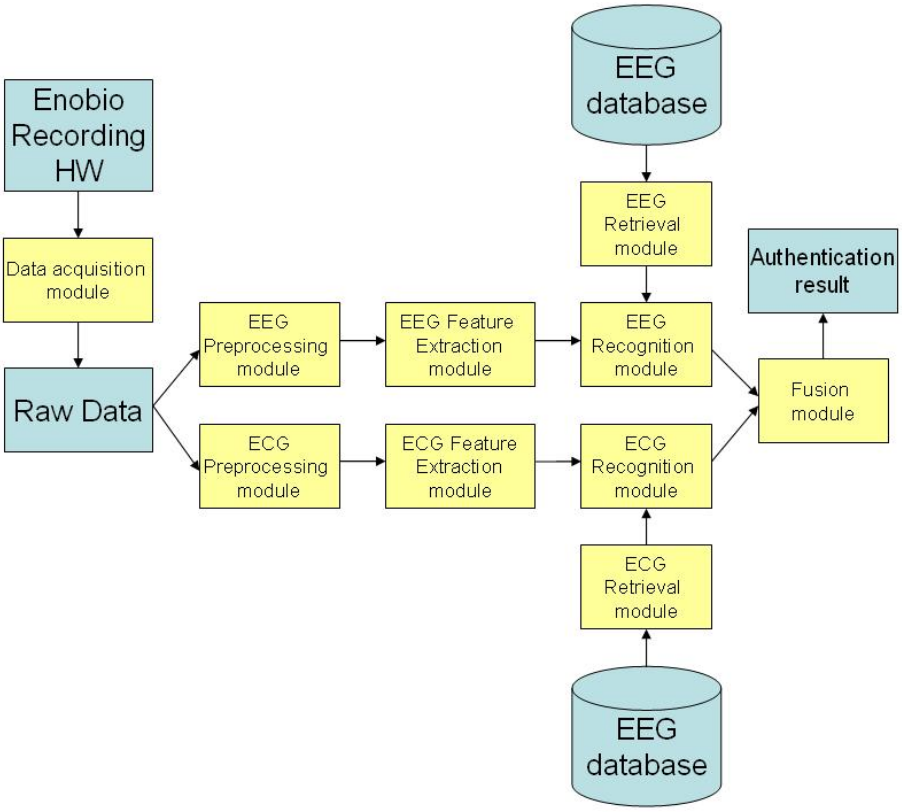
Fig. 1.4 The data acquisition module is the software that controls the ENOBIO sensor in order to capture the raw data. Remember that 4 channel are recorded: 2 EEG channels placed in the forehead, 1 ECG channel placed in the left wrist and 1 electrode placed in the right earlobe for referencing the data. At this point the data is separate in EEG data and ECG data and sent to two parallel but different biometric modules for EEG and ECG. Each pre-processing module is explained in detail in the respective pre-processing sections. Then the features are extracted. A detailed explanation of the features used in each module is found in the features sections. For the signature extraction module, four 3-minutes takes are needed. The signature extraction module is explained in detail in the enrolment subsection. Once the signatures are extracted, they are both stored in their respective database for further retrieval when an authentication process takes place.



Since the earlobe is a position with no electrical activity, and it is very easy and unobtrusive to place an electrode there with the help of a clip, this site appeared the better one to reference the rest of electrodes. After referencing, a second order pass band filter with cut off frequencies 0.5 and 40 Hz is applied.

Once the filters are applied, the whole signal is segmented in 4 second epochs. Artefacts are kept, in order to ensure that only one minute of EEG data will be used for testing the system. We remind the reader that the subject is asked to close his/her eyes in order to minimize eye related artefacts.

Fig. 1.5 The flowchart is identical to the enrolment one until the Feature Extraction Module. One diference that is not shown in the scheme is that now we only record 1 minute of data. The recognition module retrieves the claimed subjects EEG and ECG signature from their respective databases. At this point we have the probability that the 1-minute EEG recorded belongs to the claimed subject. We also have the probability that the 1-minute ECG recorded belongs to the claimed subject. The fusion module then takes care to fusion these probabilities to obtain a very confident decision.



1.3.2 Features extracted from EEG

We conducted an intensive preliminary analysis on the discrimination performance of a large initial set of features, e.g. Higuchi fractal dimension, entropy, skewness, kurtosis, mean and standard deviation. We chose the five ones that showed a higher discriminative power. These five different features were extracted from each 4-second epoch and input into our classifier module. All the mentioned features are simultaneously computed in the biometry system presented herein. This is what we denote as the multi-feature set. The features are detailed in the following.

We can distinguish between two major types of features with respect to the number of EEG channels employed in their computation. Therefore we can group features in single channel features and two channels ones (the synchronicity features).

1.3.2.1 One channel features. Autoregression (AR) and Fourier transform (FT) are the implemented single channel features. They are calculated for each channel without taking into account the other channel. The usage of these features for EEG biometry is not novel [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. However we describe them for the sake of completeness.

A **Autoregression**

We use the standard methodology of making an autoregression on the EEG signal and the resulting coefficients as features. The employed autoregression is based on the Yule-Walker method, which fits a pth order AR model to the windowed input signal, X(t), by minimizing the forward prediction error in a least-square sense. The resulting Yule-Walker equations are solved through the Levinson-Durbin recursion. The AR model can be formulated as:

$$X(t) = \sum_{i=1}^{n} a(i)X(t-i) + e(t) \tag{1.1}$$

We take n=100 based on the discrimination power obtained in some preliminary works.

B **Fourier transform**

The well-known Discrete Fourier Transform (DFT), with expression

$$X(k) = \sum_{j=1}^{N} x(j)\omega_N^{(j-1)(k-1)} \tag{1.2}$$

$$x(j) = \frac{1}{N}\sum_{k=1}^{N} X(k)\omega_N^{-(j-1)(k-1)} \tag{1.3}$$

where

$$\omega_N = e^{\frac{-2\pi i}{N}} \tag{1.4}$$

1.3.2.2 Synchronicity features. Mutual information (MI), coherence (CO) and cross correlation (CC) are examples of two-channel features related to synchronicity [19, 20, 21]. They represent some join characteristic of the two channels involved in the computation. This type of features is used for the first time here.

A **Mutual information**

The mutual information [12, 21] feature measures the dependency degree between two random variables given in bits, when logarithms of base 2 are used in its computation.

The MI can be defined as:

$$MI_{xy} = E(x) + E(y) - E(xy) \tag{1.5}$$

where E is the entropy operator: E(x) is the entropy of signal x and E(x,y) is the joint entropy of signals x and y.

B **Coherence**

The coherence measure quantizes the correlation between two time series at different frequencies [19, 20]. The magnitude of the squared coherence estimate is a frequency function with values ranging from 0 to1.

The coherence Cxy(f) is a function of the power spectral density (Pxx and Pyy) of x and y and the cross power spectral density (Pxy) of x and y, as defined in the following expression:

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \tag{1.6}$$

In this case, the feature is represented by the set of points of the coherence function.

C **Correlation measures**

The well-known correlation (CC) is a measure of the similarity of two signals, commonly used to find occurrences of a known signal in an unknown one with applications in pattern recognition and cryptanalysis [13]. We calculate the autocorrelation of both channels, and the cross-correlation between them

following:

$$CC_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E((X-\mu_X)(Y-\mu_Y))}{\sigma_X \sigma_Y} \tag{1.7}$$

where E() is the expectation operator, cov() the covariance one, and μ and σ, the corresponding mean and standard deviations values.

1.3.3 EEG Authentication Methodology

The work presented herein is based on the classical Fisher's Discriminant Analysis (DA). DA seeks a number of projection directions that are efficient for discrimination, i.e., separation in classes.

It is an exploratory method of data evaluation performed as a two-stage process. First the total variance/covariance matrix for all variables, and the intra-class variance/covariance matrix are taken into account in the procedure. A projection matrix is computed that minimizes the variance within classes while maximizing the variance between these classes. Formally, we seek to maximize the following expression:

$$J(W) = \frac{W^t S_B W}{W^t S_W W} \tag{1.8}$$

Where:

- W is the projection matrix
- S_B is between-classes scatter matrix
- S_W is within-class scatter matrix

For an n-class problem, the DA involves n-1 discriminant functions (DFs). Thus a projection from a d-dimensional space, where d is the length of the feature vector to be classified, into a (n-1)-dimensional space, where d $\geq$ n , is achieved. Note that in our particular case, the subject and class are equivalment. In our algorithm we work with 4 different DFs:

- linear: Fits a multivariate normal density to each group, with a pooled estimate of the covariance.
- diagonal linear: Same as 'linear', except that the covariance matrices are assumed to be diagonal.
- quadratic: Fits a multivariate normal density with covariance estimates stratified by group.

- diagonal quadratic: Same as 'quadratic', except that the covariance matrices are assumed to be diagonal.

The interested reader can find more information about DA in [13].

Taking into account the 4 DF's, the 2 channels, the 2 single channel features and 3 synchronicity features, we have a total of 28 different classifiers. Here, we mean by classifier each of the 28 possible combinations of feature, DF and channel. All these combinations are shown in the next table:

We use an approach that we denote as 'personal classifier', which is explained herein, for the identity authentication case: the 5 best classifiers, i.e., the ones with more discriminative power, are used for each subject. When a test subject claims to be, for example, subject 1, the 5 best classifiers for subject 1 are used to do the classification. The methodology applied to do so is explained in the next section.

ENROLMENT PROCESS:

In order to select the 5 best classifiers for the N enrolled subjects with 4 EEG takes, we proceed as follows. We use the 3 first takes of the N subjects for training each classifier and the 4th take of a given subject is used for testing it. We repeat this process making all possible combinations (using one take for testing and the others for training). Each time we do this process, we obtain a classification rate (CR): number of feature vectors correctly classified over the total number of feature vectors. The total number of feature vectors is around 45, depending on the duration of the take (we remind the reader that the enroent takes have a duration of approximately 3 minutes, and these takes are segmented in 4-second epochs). Once this process is repeated for all 28 classifiers, we compute a score measure on them, which can be defined as:

$$score = \frac{average(CR)}{standard\ deviation(CR)} \tag{1.9}$$

The 5 classifiers with higher scores out of the 28 possible classifiers are the selected ones. We repeat this process for the N enrolled subjects.

AUTHENTICATION PROCESS

Once we have the 5 best classifiers for all the N enrolled subjects, we can then implement and test our final application. We now proceed in a similar way, but we only use one minute of recording data, i.e., we input in each one of the 5 best classifiers 15 feature vectors (we remind the reader that the authentication test takes have a duration of 1 minute, and these takes, as we did in the enroent case, are segmented in

Table 1.1 List of possible classifiers used in our system. Note that the MI, CO and CC features are extracted from both channels so the field channel is omitted in these cases

Classifier ID	Feature*	channel	discriminant Function
1	AR	1	linear
2	AR	1	diagonal linear
3	AR	1	quadratic
4	AR	1	diagonal quadratic
5	AR	2	linear
6	AR	2	diagonal linear
7	AR	2	quadratic
8	AR	2	diagonal quadratic
9	FT	1	linear
10	FT	1	diagonal linear
11	FT	1	quadratic
12	FT	1	diagonal quadratic
13	FT	2	linear
14	FT	2	diagonal linear
15	FT	2	quadratic
16	FT	2	diagonal quadratic
17	MI	-	linear
18	MI	-	diagonal linear
19	MI	-	quadratic
20	MI	-	diagonal quadratic
21	CO	-	linear
22	CO	-	diagonal linear
23	CO	-	quadratic
24	CO	-	diagonal quadratic
25	CC	-	linear
26	CC	-	diagonal linear
27	CC	-	quadratic
28	CC	-	diagonal quadratic

*AR = Autoregression
FT = Fourier Transform
MI = Mutual Information
CO = Coherence
CC = Cross Correlation

4-second epochs). Each classifier outputs a posterior matrix (Table 1.2). In order to fuse the results of the 5 classifiers, we vertically concatenate the 5 obtained posterior matrices and take the column average. The resulting vector is the one we will use to take the authentication decision. In fact, it is a Probability Density Function (PDF). See Figure 1.6 and 1.7):

- The 1st element is the probability that the single minute test data comes from subject 1.
- The 2nd element is the probability that the single minute test data comes from subject 2
- etc...

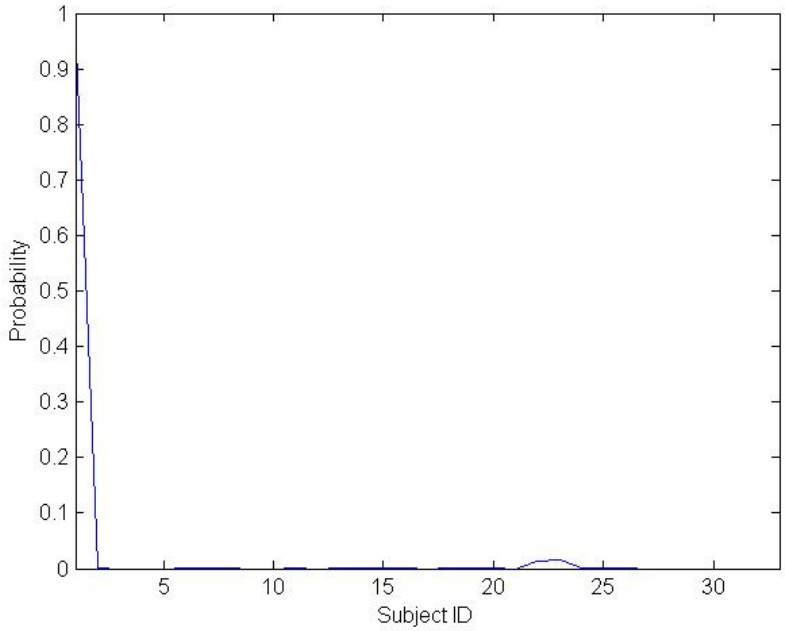
Table 1.2 Posterior matrix of the 15 FT feature vectors extracted from one minute EEG recording of subject 1. Each row represents the probabilities assigned to each class for each feature vector. We see that the subject is well classified as being subject 1 (refer to the last row). Notice that, for simplicity, this posterior matrix represents a 5-class problem (i.e., 4 reference subjects in this case). In our real system, we work with a 33-class problem.

Classified as	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5
Test 1	0.46	0.28	0	0	0.23
Test 2	0.40	0.24	0	0.23	0.11
Test 3	0.99	0	0	0	0.01
Test 4	0.99	0	0	0	0
Test 5	0.99	0	0	0	0
Test 6	0.91	0.01	0.04	0	0.04
Test 7	0.99	0	0	0	0
Test 8	0.99	0.01	0	0	0
Test 9	0.96	0.02	0.02	0	0
Test 10	0.99	0	0	0	0
Test 11	0.16	0.04	0.25	0.53	0
Test 12	0.53	0.35	0	0	0.11
Test 13	0.92	0.07	0	0	0.01
Test 14	0.99	0	0	0	0
Test 15	1	0	0	0	0
average	0.81	0.07	0.02	0.05	0.03

The last step in our algorithm takes into consideration a decision rule over the averaged PDF. We use a threshold applied on the probability of the claimed subject. If the probability of the claimed subject is higher than the applied threshold, then the authentication result is positive. Three values are output by our algorithm:

- binary decision (authentication result)
- score (probability of the claimed subject)
- confidence level (an empiric function that maps the difference between threshold and score to a percentage)

Fig. 1.6 PDF for one of the enrolled subjects. The subject is classified against his training data set (class 1) and the training data sets of the reference subjects (from class 2 to class 33). In this example, he/she will be correctly authenticated with a high confidence level

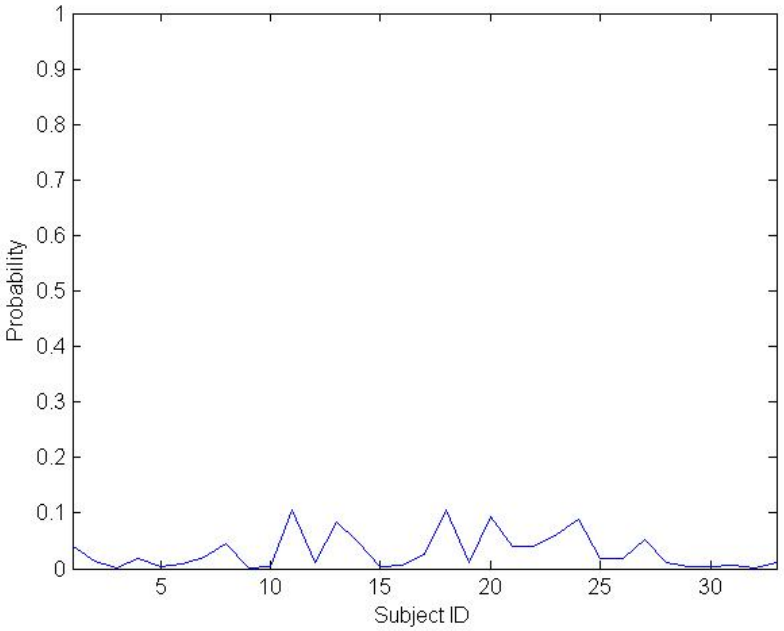


In order to evaluate the performance of the system, we proceed as follows. 32 subjects with three 3-minutes takes are used as reference subjects and the other 8 subjects with four 3-minute takes are enrolled in the system as explained in the 'enrolment process' above. For the system testing, we distinguish three cases: when a subject claims to be himself (legal situation) and when a subject claims to be another subject from the database (impostor situation). We have 48 legal situations, 350 impostor situations and 16 intruder situations. What we do, in order to take all the profit from our data, is to make all the possible combinations with the authentication takes. Subject 1 will claim to be subject 1 (legal situation), but he will also claim to be all the other enrolled subjects (impostor situation). An intruder will claim to be all the 8 enrolled subject, one by one. The False Acceptance Rate (FAR) is computed taking into account both the intruder and the impostor cases. The True Acceptance Rate (TAR) only takes into account the legal cases.

The performance of the EEG system using a probability threshold of 0.1 is:

- TAR=79,2%

Fig. 1.7 PDF for an impostor situation. In this case the probabilities are more or less evenly distributed among all classes: the one he claims to be (class 1) and the other reference subject classes (from class 2 to class 33), so in this case he/she will not be authenticated with a high confidence level



- FAR=21,8%

This threshold places our system close to the Equal Error Rate (EER) working point. By definition, at the EER working point the following equation is valid:

$$TAR + FAR = 100\% \tag{1.10}$$

and the compromise between the highest TAR and the lowest FAR is optimal.

1.4 AUTHENTICATION ALGORITHM BASED ON ECG

1.4.1 ECG pre-preprocessing

We reference the ECG channel placed in the left wrist to the right earlobe reference channel. A first difference with the EEG pre-processing is that, in this case, we are

not using 4-seconds epochs. Now, we segment each single heart beat waveform from the ECG signal.

1.4.2 Heart beat waveform as unique feature from ECG

From a large set of different features (Heart Rate Variability related features, geometric features, entropy, fractal dimension and energy), we finally only use the heart beat waveform as input feature in our classifiers, since it is the one that showed the higher discriminative power between subjects.

As previously said, from each minute of data we extract each single heart waveform. For defining the heart beat waveform feature, we decimate to a 144 length vectors. All these vectors in their totality are the heart beat waveform features. Thus, the total number of feature vectors, in this case, depends on the number of heart beat in one minute, i.e., on the heart beat rate.

1.4.3 ECG Authentication Methodology

The authentication methodology is very similar to the one used in EEG. The difference is that now we only have one feature, but we still have 4 DF's, so at the 'best classifier selection' stage, what we do is to select the best DF for each subject. In this modality there is no data fusion. Once the best DF is found, then the classification is made for the 'heart beat shape' feature and for the selected DF.

The outputs for this modality are the same:

- binary decision (authentication result)
- score (probability of the claimed subject)
- confidence level (an empiric function that maps the difference between threshold and score to a percentage)

The performance of the ECG system using a probability threshold of 0.6:

- TPR=97.9%
- FPR=2.1%

This threshold places the performance of our system on the EER working point, as explained in the EEG Authentication Methodology section.

1.5 EEG AND ECG FUSION

At this stage, we have the elements that could lead the system to take a decision based on each of the two modalities. However we have observed that the application of a

decision fusion increases the reliability of the final system in terms of acceptance and rejection rates. In order to achieve the maximum performance of the system, we fuse therefore the results of the EEG and the ECG authentication systems. As both signals are independent and the recording protocols, completely compatible with each other, it is very easy to register both EEG and ECG at the same time with the ENOBIO sensor.

Figure 1.8 shows the bidimensional decision space where the scores probabilities for ECG and EEG are plotted one against the other. As it can be observed the inclusion of both modalities together with their fusion makes the two classes linearly separable. Indeed we can undertake the separation through a surface formally expressed as:

$$\phi_1 = mE + c - C \tag{1.11}$$

where E and C state for the scores probabilities of the claimed subjects respectively for the EEG and ECG modalities, m and c, for the parameters of the lineal decision boundary, and ϕ_1 for this decision boundary. Values over d will be considered as legal subjects, whereas those under d, are classified as impostors as shown in Figure 1.8, where the decision boundary labeled as 1 has been adapted to the test on hand. Such a linear decision surface is easy to optimize, because it lives in a low parametrical space.

One more decision surface ϕ_2 is depicted in Figure 1.8. The relationship between adaptation and generalization capability of a classifier system is very well-known. Therefore ϕ_2 is much more adapted to the test data set used in the simulation presented herein. We expect such a decision boundary to present less generalization capability when new subjects enter into the system. However the performance of ϕ_1 is good enough for a practicable biometric system and furthermore, easier to parameterize.

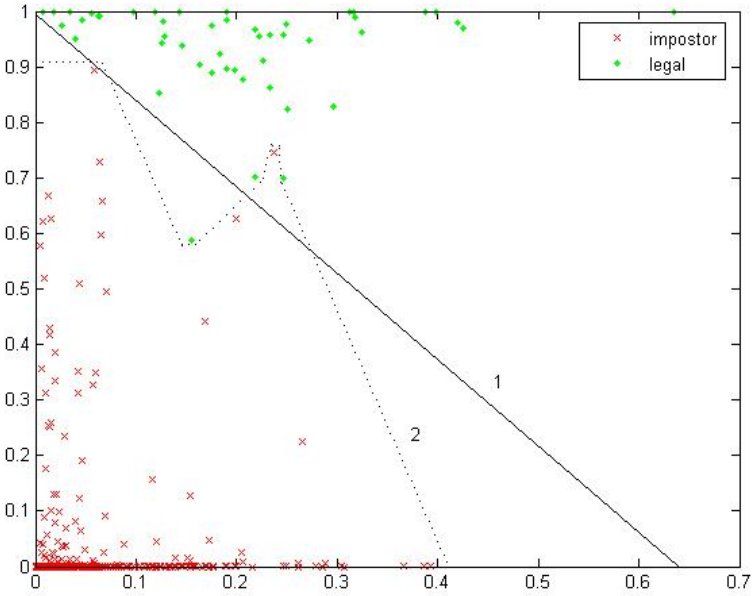
From an application point of view, the decision surface 1 will be useful for a application where security issues are not critical (e.g. access to Disneyland, where we are interested that everybody is authenticated even thought some intruders get also access to the facilities), while the surface 2 would be used in an application where the security issues are extremely important (e.g. access to radioactive combustible in a nuclear plant, where we really do not want any intruder to get access, even thought some legal subject are not allowed to get access).

The results in terms of TPR and FPR are shown in Table 2.

Table 1.3 Final results after fusion

	TPR	FPR
decision function 1	97.9%	0.82
decision function 2	100	0

Fig. 1.8 Bidimensional decision space. Ordinates represent the ECG probabilities and the abscises the EEG probabilities. Red crosses represent impostor cases and green crosses represents legal cases. Two decision functions are represented



1.6 CONCLUSION

We have presented the performance results obtained by a bi-modal biometric system based on physiological signals, namely EEG and ECG. The results demonstrate the validity of the multi-stage fusion approach taken into account in the system. In this context we undertake fusion at the feature, classification and the decision stages improving this way the overall performance of the system in terms of acceptance and rejection rates.

Moreover, the system presented herein improves the unobtrusiveness of other biometric systems based on physiological signals due to the employment of a wireless acquisition unit (ENOBIO). Moreover two channels were used for the EEG modality and one channel for ECG.

It is worth mentioning the implementation of novel EEG features. The inclusion of synchronicity features, which take into account the data of two different channels, complement quite well the usage of one channel features, which have been traditionally used in biometric systems. On the other hand those two channel features are

used for the first time in such a system. The features undergo a LDA classification with different discriminant functions. Therefore we take into consideration a set of feature-classifiers combinations. This fact improves the robustness of the system and even its performance.

After testing the performance of different ECG features we conclude that the most discriminative one is the heart beat waveform as a whole. For its extraction it is necessary to implement a pre-processing stage. The unique feature undergoes a classification stage similar to the one used with the modality described above. Therefore different discriminant functions of a LDA classifier present different performance for each of the subjects. The inclusion of their combination results in an improvement in the performance of the overall system.

We have demonstrated as well the suitability of including a decision fusion stage, whereby the decision between legal and impostor subjects becomes linear. Moreover the decision fusion allows to decrease the FPR of the system, which constitutes an important feature of a reliable system. Although the corresponding decision boundary was computed on hand of test results, its parameterization is easily attainable. Optimization procedures can be applied to fulfill this aim.

We also wish to mention other possible future applications of our system. Using the ENOBIO sensor, which is unobtrusive and wearable, and through the analysis of EEG and ECG signal, we can not only authenticate the subjects. There are evidences that both EEG and ECG signals can be used to validate the initial state of the subject, that is to detect if the subject is in normal condition and has not taken alcohol, drugs or not suffering from sleep deprivation [26, 27, 28]. Moreover, a continuous authentication system and a continuous monitoring system could also be implemented since the sensor, as already explained, is unobtrusive and wearable.

A further step is to extract emotions from ECG and EEG [29, 30]. This would be very useful for human-computer interactions. As an example, we can think on virtual reality applications where the reactions of the computer generated avatars would take into account the emotions of the subject immersed in the virtual reality environment [32].

1.7 SUMMARY

Features extracted from electroencephalogram (EEG) and electrocardiogram (ECG) recordings have proved to be unique enough between subjects for biometric applications. We show here that biometry based on these recordings offers a novel way to robustly authenticate subjects. In this paper, we presented a rapid and unobtrusive authentication method that only uses 2 frontal electrodes (for EEG recording) and another electrode placed on the left wrist referenced to another one placed at the right earlobe. Moreover the system makes use of a multi-stage fusion architecture,

which demonstrates to improve the system performance. The performance analysis of the system presented in this paper stems from an experiment with 40 subjects, from which 8 are used as enroled test subjects and 32 are used as reference subjects needed for both, the enrolment and the authentication process.

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The authors also wish to thank the HUMABIO project (Contract number 026990) who funded part of the research explained in this chapter. HUMABIO is a EC co-funded "Specific Targeted Research Project" (STREP) where new types of biometrics are combined with state of the art sensorial technologies in order to enhance security in a wide spectrum of applications like transportation safety and continuous authentication in safety critical environments like laboratories, airports and/or other buildings.

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Appendix D

Electrophysiological Biometrics: Opportunities and Risks

This enclosed work that follows was published as a chapter in a book called "Second Generation Biometrics" published by Springer in 2010. For complete reference please see Riera et al. [31].

15 Electrophysiological Biometrics: Opportunities and Risks.

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Abstract The use of electrophysiological signals as features to authenticate subjects is a novel approach to biometrics. It has been proven that both electrocardiography (ECG) and electroencephalography (EEG) signals are unique enough to be applied for recognition and identification purposes. Moreover, the use of electrooculography (EOG) and electromyography (EMG), which are related to the movement of the eyes and muscular activity, can also be useful and add an extra dimension to the field of biometrics: the possibility of continuous and transparent biometrics, i.e., biometry on the move. We also comment on the future of the electrophysiological biometrics, highlighting the added value. This includes the use of a Brain Computer Interface (BCI) system for authentication purposes and the application of such a system for the evolving field of telepresence and virtual reality.

Acknowledgments The authors wish to acknowledge the ACTIBIO project, a STREP collaborative project supported under the 7th Framework Program (Grant agreement number: FP7-ICT-2007-1-215372) in which Starlab is actively involved. ACTIBIO aims at authenticating subjects in a transparent way by monitoring their activities by means of novel biometric modalities.

List of abbreviations:

AR	Autoregression
BCI	Brain Computer Interface
CC	Cross Correlation
CO	Coherence
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
ERP	Event Related Potential
EU	European Union
FT	Fourier Transform
FP	Framework Program
Hz	Hertz
MI	Mutual Information
USB	Universal Serial Bus

Introduction

The market of biometry is growing every year, as a result of the great interest in this field, mainly for security reasons. The use of electrophysiological signals for biometric purposes is a novel approach and offers some advantages compared to more classical biometric modalities such as fingerprinting and retina or voice recognition. For instance, continuous authentication can be performed as long as the subject is wearing the recording electrodes. Moreover, EEG, ECG and EMG (all variants of electrophysiology) can also provide information about the emotional state, sleepiness/fatigue level, the stress level, and continuously monitor the vital signals of the subject, which could also be useful for preventive medicine and telemedicine.

The chapter is organized as follows. The next subsection explains the two main concepts of this text: electrophysiology and biometry. Then the concept of electrophysiological biometrics is provided. This section finishes with a discussion of the advantages of electrophysiological biometrics over more classical biometric modalities. The second section -'Biometric Technology'- is divided in six subsections. 'Artifact rejection/correction' explains our approach to reduce this undesirable noise that corrupts virtually all the electrophysiological recordings. 'EEG', 'ECG', 'EOG' and 'EMG' describe respectively the corresponding biometric modalities we have implemented. The last point of this section, 'BCI', describes a new biometric approach based on the control of a brain computer interface. Next section, 'Multimodal System: Fusion' deals with the fusion of the different modalities in order to extract a more reliable biometric result. The two next sections explain the 'Technology Trends and Opportunities' and the 'Vision for the Future and Risks'. The last section summarizes this chapter.

Electrophysiological Biometrics.

What is electrophysiology?

Electrophysiology is the study of the electrical properties of biological cells and tissues. Several techniques have been developed depending on the scale we want to record: from patch-clamp techniques for single cells or even ion channels to electrocardiography or electroencephalography for whole organs such as the heart or the brain, respectively.

Many particular electrophysiological readings have specific names, referring to the origin of the bioelectrical signals:

- Electrocardiography (ECG) - for the heart
- Electroencephalography (EEG) - for the brain
- Electrocorticography (ECoG) - from the cerebral cortex
- Electromyography (EMG)- for the muscles
- Electrooculography (EOG)- for the eyes
- Electroretinography - for the retina
- Electroantennography - for the olfactory receptors in arthropods
- Audiology - for the auditory system

In this chapter we will study the biometric potential of ECG, EEG, EMG and EOG. These electrophysiological modalities can be easily recorded by placing some electrodes in the skin of the subject, making them less obtrusive than for instance ECoG. The electrode configuration and the basic principles of each one of these modalities will be explained in their respective sections, but in order to show the importance of such techniques, it is interesting to mention the following facts:

As soon as 1872, the first ECG was recorded by Alexander Birmick Muirhead, but it was not until the work of Waller (Waller 1887) that the ECG was studied in a more systematic way. Finally, the invention of the string galvanometer by Willem Einthoven (Moukabary, 2007) supposed a breakthrough in the study of the ECG. His works were awarded with a Nobel Prize in Medicine in 1924.

A good timeline history of EEG is provided by Schwartz (Schwartz, 1998). The first findings were presented in 1875 by Richard Caton. He recorded the EEG signals of the exposed cerebral hemispheres of rabbits and monkeys. The first EEG recorded to a human is credited to Hans Berger in 1920.

The first recording of EMG was made in 1890 by Marey, although since 1666 it was known that certain specialized muscles produce electricity. In 1791, Galvanni demonstrated that electricity could initiate muscle contractions (Galvanni, 1791).

Finally, the developers of the patch-clamp technique, Erwin Neher and Bert Sakmann (Neher & Sakmann, 1992), received the Nobel Prize in 1991. Briefly, this technique allows the study of a single or several ion channels present in some types of cells by the use of an electrode and a micropipette.

What is biometry?

The term biometrics has a Greek origin: it is composed by the words “bios” (life) and “metron” (measure). A biometric identifier is originally defined as the objective measurement of physical characteristics. The term has been used in medicine, biology, agriculture and pharmacy (e.g. in biology, biometrics is a branch that studies biological phenomena and observations by means of statistical analysis).

The term biometrics here refers to automated methods and techniques that analyze human characteristics in order to recognize a person, or distinguish this person from another, based on a physiological or behavioral characteristic.

Another meaning has also been acquired in the last decades, focused on the characteristic to be measured rather than the technique or methodology used (Zhang 2000): “A biometrics is a unique, measurable characteristic or trait of a human being for automatically recognizing or verifying identity.”

A biometric trait ideally satisfies the following requirements:
Universal: Each user should have it.

Unique: In order for something to be unique, it has to be the only existing one of its type, have no like or equal, be different from all others. When trying to identify an individual with certainty, it is absolutely essential to find something that is unique / distinctive to that person.

Measurable: In order for recognition to be reliable, the characteristic being used must be relatively static and easily quantifiable.

Permanent: Traits that change significantly with time, age, environment conditions or other variables are of course not suitable for biometrics.

Characteristic or trait: The measurable physical or personal behavioral pattern used to recognize a human being. Currently, identity is often confirmed by something a person has, such as a card or token, or something the person knows, such as a password or a personal identification number. Biometrics involves something a person is or does. These types of characteristics or traits are intrinsic to a person, and can be approximately divided into physiological and behavioral.

Physiological characteristics refer to what the person is, or, in other words, they measure physical parameters of a certain part of the body. Some examples are fingerprints, that use skin ridges, face recognition, using the shape and relative positions of face elements, retina scanning, etc. Behavioral characteristics are related to what a person does, or how the person uses the body. Voice or gait recognition, and keystroke dynamics, are examples of this group.

Robust: Intra – class variability should be as small as possible, which means that different captured patterns from the same user should be as close as possible.

Accessible: it should be easy to present to the sensor.

Acceptable: it should be well accepted by the public – non obtrusive and non intrusive.

Hard to circumvent: it should be difficult to alter or reproduce by an impostor who wants to fool the system.

Moreover the recognition system should be automatic, i.e. must work by itself, without direct human intervention. For a biometric technology to be considered automatic, it must recognize or verify a human characteristic in a reasonable time and without a high level of human involvement.

A biometric recognition system has two main operational modes: verification (or authentication) and identification. Recognition refers to no particular operational mode, as we now discuss.

Verification: To verify something is to confirm its truth or establish its correctness. In the field of biometrics, verification is the act of proving the claim made by a person about their identity. A computer system can be designed and trained to compare a biometrics presented by a person against a stored sample previously provided by that person and identified as such. If the two samples match, the system confirms or authenticates the individual as the owner of the biometrics on file.

Identification: Identity is the answer to the question about who a person is, or the qualities of a person or group which make them different from others, i.e., being a specific person. Identity can be understood either as the distinct personality of an individual regarded as a persistent entity, or as the individual characteristics by which this person is recognized or known. Identification is the process of associating or linking specific data with a particular person.

Recognition: To recognize someone is to identify them as someone who is known, or to distinguish someone because you have seen, heard or experienced them before (to "know again"). A person cannot recognize someone who is completely unknown to them. A computer system can be designed and trained to recognize a person based on a biometric characteristic, comparing a biometric presented by a person against biometric samples stored in a database If the presented biometric matches a sample on the file, the system then recognizes the person.

Depending on the application context, a biometric system may operate either in authentication mode or identification mode.The probability of having a false true value for the authorization of a subject is higher with identification than with authentication, and thus the later is preferable, especially for high level security requirements. The block diagrams of an authentication system and an identification system are depicted in Figure 1; user enrolment, which is common to both the tasks is also graphically illustrated.

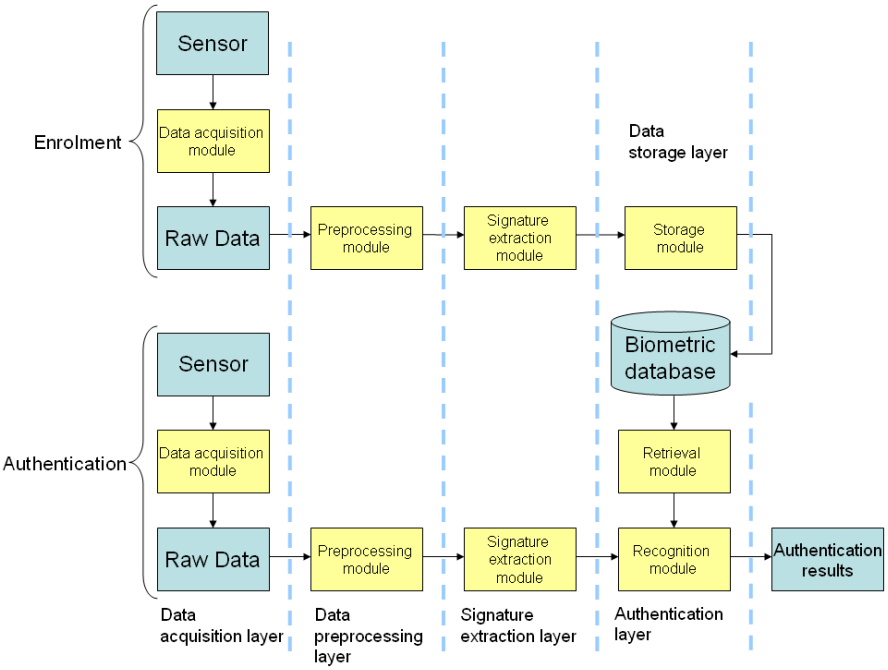

Fig. 1: Common architecture of a biometric system.

Throughout this chapter, we will use the generic term recognition where we do not wish to make a distinction between authentication and identification. Some other expressions frequently used in biometrics that are worth defining here:

Biometric sample: Biometric samples or data are biometric information presented by the user and captured by the biometric system.

Biometric template: A biometric template is the individual mathematic data set calculated from a biometric sample. Biometric systems need templates for comparison.

Biometric system: A biometric system is an automated system capable of capturing a biometric sample, extracting biometric data, comparing it with other biometric data and deciding whether or not the recognition process has been successful.

Biometric technology: In the present study the term biometric technologies refers to all computer-based methods to recognize human beings using biometric characteristics.

How can electrophysiological signals be used for biometry?

Now that the two main concepts of this chapter, biometry and electrophysiology, have been explained, we can link them in order to explain our approach to biometrics. We have used four electrophysiological signals: EEG, ECG, EMG and EOG. Another approach based on a BCI has been also been explored. What are the advantages of using these signals in the field of biometrics? First of all, it is interesting to note that every living person has an active brain and a heart beat, making those signals completely universal. Typical biometric traits, such as fingerprint, voice, and retina, are not universal, and can be subject to physical damage (dry skin, scars, loss of voice, etc.). In fact, it is estimated that 2–3% of the population is missing the feature that is required for the authentication, or that the provided biometric sample is of poor quality.

It has been proven that the EEG and ECG are unique enough to be used for biometric purposes (Marcel, 2005; Mohammadi, 2006; Paranjape, 2001; Poulos, 1998; Poulos, 1999; Poulos, 2001; Poulos, 2002; Riera, 2008, Biel, 2001; Chang, 2005; Israel, 2005; Kyoso, 2001; Palaniappan, 2004). In fact, if we think on the huge number of neurons present in a typical adult brain (10^11) and their number of connections (10^15), we can definitively claim that no 2 brain are identical. A similar argumentation could be done for the heart.

From a more philosophical point of view, we can also think on what the ultimate biometric system will be like. That is, the one that will be impossible to spoof (or almost). This question is clearly related to the issue of where our identity lies. An intuitive answer to this question is that our identity must lie in the brain, or, to be a bit broader, in our Central Nervous System. We could replace our fingertips and hearts or have a face-lift and retain our identities, but replacing somebody's brain will distort our conception of spoofing in a radical way. If we could "clone" somebody's brain, then one could argue that we can no longer say that person is not the real person. At any rate, the reader will agree with the statement that "the ultimate seat of identity lies in the living, dynamic brain", or, at least, in part of it (e.g., in the abstract set of neuronal connections). In recent work we have advanced a great deal in the development of physiologically based biometric systems exploiting EEG (Marcel, 2005; Mohammadi, 2006; Paranjape, 2001; Poulos, 1998; Poulos, 1999; Poulos, 2001; Poulos, 2002; Riera, 2008) and ECG (Biel, 2001; Chang, 2005; Israel, 2005; Kyoso, 2001; Palaniappan, 2004) signals and classification algorithms. The derived systems rely on spontaneously generated electrophysiological signals, and as such they are in some sense weaker to spoofing attacks than they could be. After all, one could record EEG/ECG spontaneous activity and play it back during authentication. This would be hard, but not impossible. If one were free to challenge the impostor asking for different features of their EEG, or to stimulate the subject and study the response of their brains, the biometric system would become much more robust.

On the other hand, physiologically based systems are bound to be more obtrusive than other ones (especially EEG), so they must provide a substantial added value in relation to others (Graff, 2007) and minimize the intrusiveness as much as possible by applying wearable electrophysiological recording devices (Ruffini, 2006; Ruffini, 2007). Another element of interest is that biometrics technologies will definitely become very important in immersive interactive environments, where we will be able to control voice, body, gestures, etc. How will others know that you are you, and not an avatar controlled by somebody else, or, worse yet, an agent?

What are the comparative advantages of electrophysiological biometrics?

Electrophysiological biometrics has an advantage over the classical biometric modalities. Normally a biometric system is used in order to access a secure area or in order to unlock a computer, for instance. This scenario is called initial authentication and it is the typical scenario used with fingerprint authentication (there are laptops in the market that incorporate a fingerprint authentication system in order to unlock the computer). On the other hand, by wearing a band set with bioelectrodes, the biometric characteristic can be recorded in real time, and for long periods of time, thus permitting the biometric system to continuously

authenticate the user. For instance, once the computer is unlocked, the system is still extracting the biometric features, and this way a impostor could not use such a system, even if it was unlocked in the previously by the legal user.

In order to make the system accepted by the users, it should be as transparent as possible. ENOBIO is a sensor developed by Starlab Barcelona SL with interesting features: it is wearable, wireless and can work in dry mode, that is, without the need to use conductive gel. It consists of 4 electrodes and a unit which can be worn as a head band. The unit has all the electronics and a radio that transmit the recorded data wirelessly to the receiver that is connected to a computer by a USB connection. We can see the electrodes and the recording unit placed with the headband in figure 2.

Fig. 2: Enobio Sensor**.**

In order to record ECG, an electrode can be placed in the left wrist with a longer cable and with the help of a band.

Besides being able to perform a continuous authentication, we can also perform what we call *biometry on the move*. That is being able to authenticate subjects while they are moving about and not performing any specific protocol. Regarding other biometric modalities such as the ones based on fingerprint or iris recognition, the subjects have to place their finger or retina in a specific place for a specific amount of time. This fact is not always well accepted by the users, since they lose time and, specifically for iris, people do not like to place their eyes in front of a camera. With electrophysiological biometrics, the opportunity to record continuously allows the user to be authenticated on the move, thus not loosing time while undertaken the recognition.

Methods for recording electrophysiological biosignals

A suggestion would be to add a new subsection here referred in general to the methods used for recording the physiological biosignals. Before explaining the artifacts I believe that the reader should firstly be briefly informed about the signal (what is this signal) and how it is measured.

Artifact Rejection/Correction

In order for continuous authentication to take place, we face a very well known problem by electrophysiologists: the artifacts. These are electrical signals originating in places other than the desired one (e.g., electrical activity of the brain). The can originate, for example, from the electrical contact points on the skin, or from other bio-electrical sources (e.g., muscles). In all recordings, we find artifacts that can come from different sources. The artifacts can be considered as noise that do not contain, in general, useful information. The artifacts can be caused by several factors that we should take into account. It is not straightforward to distinguish among them.. In the next list we can see a list of the major categories of artifacts:

- Machine and impedance artifacts: the most common ones relates to problems with the electrode, such as the electrode itself being broke or improperly attached to the subject.
- Presence of 50 Hz artifact (or, e.e., 60 Hz in the USA), either from nearby equipment or the very common ground loop.
- Cardiac artifacts: caused by the heart
- Oculographic artifacts: caused by the movement of the eyes. The retina acts like a dipole, so it should be noted that these artifacts are not caused by the muscles that control the eyes movement, but by the movement of this dipole.
- Myographic artifacts: caused by the electrical activity of the muscles.

- Interference between biosignals: caused by capturing the electrical activity of other tissues than the ones monitored, e.g. the electrical activity of the arm muscles can influence the ECG, or of the face muscles the EEG.

In our case we are interested on the one hand in correcting the artifacts (physiological and others) from the EEG, ECG and EMG in order to have a cleaner signal and on the other hand to record the oculographic artifacts (EOG) in order to use them as a biometric signal. In the case of EMG, bipolar electrodes were placed in each forearm of the subjects so there is no presence of ECG and EOG artifacts. For each one of the EEG and ECG modalities, a different artifact corrector algorithm has been implemented. They will be explained in their respective sections.

EEG

The EEG is the recording of the brain activity by the mean of electrodes placed on the scalp of the subject. The electrical activity is due to the firing of the neurons. Many references can be found in order to find a deeper explanation regarding the EEG, such as (Kandel, 1981).

The ENOBIO sensor has been used by our team for this approach within the ACTIBIO project. Two electrodes are placed in the forehead of the subject (FP1 and FP2 locations of the 10-20 international system), and referenced to a third electrode placed in the right ear lobe. In the following figure we can see an EEG sample recorded with the ENOBIO device.

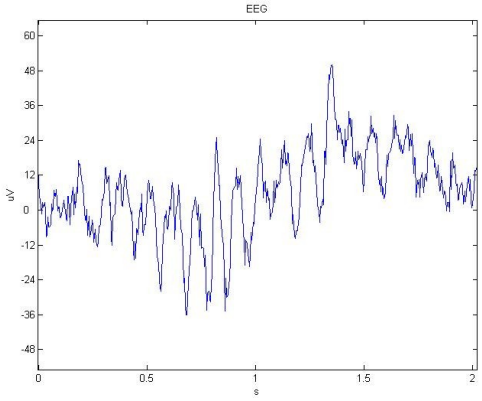

Fig. 3. ENOBIO EEG recording sample of 2 seconds with no pre-processing. The alpha wave(10 Hz characteristic EEG wave) can be seen.

Our approach to correct the artifacts is based on the detection of sudden changes in the signal and then we perform a detrending of the signal. Rather than getting in technical detail, we prefer to show the performance of the artifact corrector for each physiological signal with some figures.

In the next figure, we can see a raw EEG signal with movement artifacts (big oscillations at the beginning of the signal) and with blink artifacts (6 peaks at the end of the signal). We see that the big movement artifacts and the blink artifacts are well detected by our artifact correction module.

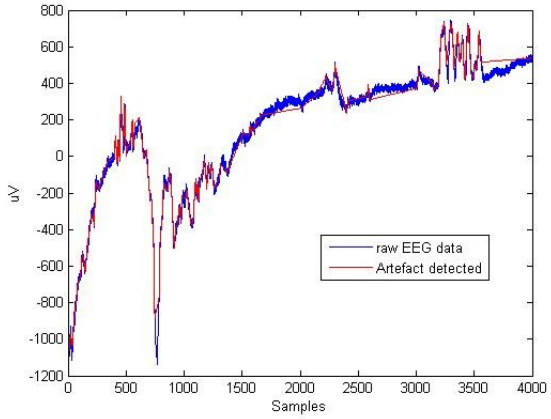

Fig.4 . Red line is the artifact estimation that will be subtracted to the raw EEG signal (black line). The algorithm works fairly well for this section.

In the following figure we can see the signal after applying the artifact corrector module. We notice that the movement artifacts (around sample 750) are still present but they are very much reduced. The same applies to the blink artifacts (around sample 3250). On the other hand, the drifts are completely removed.

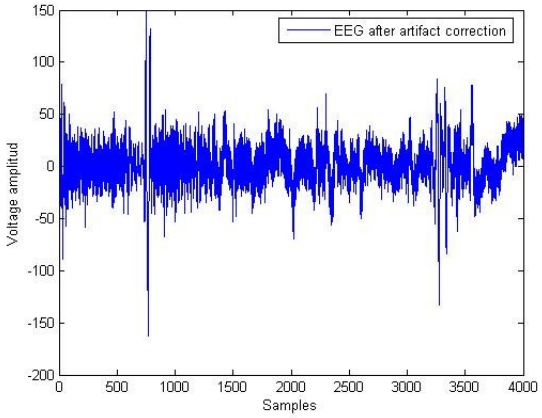

Fig. 5 EEG signal after subtracting the artifacts detected by the artifact corrector module.

Two protocols have been used. In the first one, the subjects have to stay with their eyes closed, seated on a chair, relaxed and avoiding moving. Doing so, we can minimize the eye movements and blink artifacts, and also the more general movement artifacts. The enrolment consisted of four 3-minutes takes in the same conditions.

The second protocol is much less restrictive. The subject is free to move and work in front of his or her office table, but in this first study, the subject had to remain seated. The enrolment consisted in this case of four 2-minutes takes, and the subject had to watch a movie during the recording time.

Several features were extracted. For single channel we used autoregressive coefficients (AR) and Fourier transform (FT) (4 different features since we extract AR and FF for each channel). We also extracted 3 synchronicity features: cross correlation (CC), mutual information (MI) and coherence (CO) (3 features since we extract each one of those for the 2 channels). Fisher Discriminant Analysis was used for the classification, with 4 different discriminant functions. We thus had a total of (4+3)x4=28 possible combinations between channels, features and classifiers.

Using the enrolment takes and performing a cross-fold validation over the enrolment takes, we computed the 5 best combinations per subject. We called this approach “personalized classifiers”, and indeed the performance of the system improves.

Without applying the artifact correction the results are summarized in Table 1.

Take	TPR	FPR (EER)
1	64%	36%
2	63%	37%
3	65%	35%

Table 1: Classification results of EEG (office take) without applying the artifact correction module.

As we can see the performance of the office takes shows some biometric potential, but it is not very high. The mean of the EER is 36%.

Applying the artifact corrector we see that the results improve considerably as we can see in Table 2.

Take	TPR	FPR (EER)
1	71%	29%
2	82%	18%
3	70%	30%

Table 2: Classification results of EEG applying the artifact correction module.

It is worth comparing these results with the ones acquired with the first protocol, where the subjects were asked to stay seated, relaxed and with the eyes closed. In such condition we reached an EER equal to 20%. The performance in this case is remarkably higher than in the office takes, but the recording protocol is much more obtrusive. In the second case, the subject can be freely working or doing his daily tasks while being authenticated, making such an approach much more transparent.

ECG

The ECG is recorded with the help of electrodes placed on the skin of the subject in specific places. It measures the voltage between pairs of electrodes. This voltage is generated by electrical impulses that are at the origin of the contractions of the myocardial muscle fibers. A typical schematic ECG waveform can be seen in the following figure:

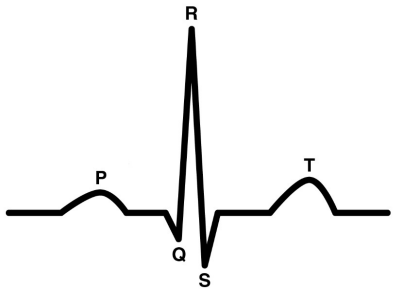

Fig. 6. A typical schematic ECG waveform. We can see the different complexes of the ECG.

In order to record ECG, we place an electrode in the left wrist of the subject, attached with the help of an elastic band. The protocols are the same described in the EEG part. In fact the ECG and EEG were recorded at the same time, since ENOBIO has 4 recording electrodes (2 for EEG, 1 for ECG and the forth one used as reference). In the following figure we can see an EEG sample recorded with the ENOBIO device.

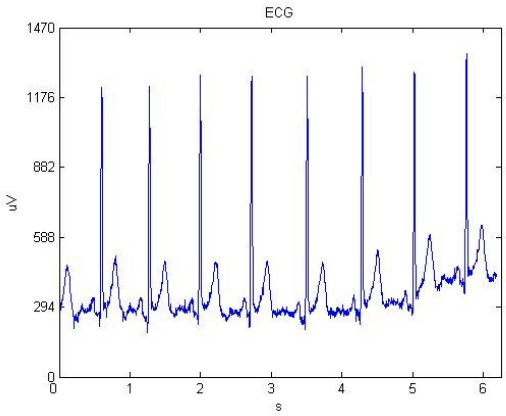

Fig. 7 ENOBIO ECG recording sample of approximately 6 seconds with no pre-processing..

The enrolment was performed at the same time and in the same conditions than the EEG enrolment (this applies for the 2 described protocols).

As in the second protocol the subjects are moving freely while seated in their office, movement artifacts appear in the ECG signal, and thus an artifact rejection module was developed specifically for this purpose. This module works by performing the following steps:

1. We apply a band pass filter with frequency cut-offs of 0.5 Hz and 35 Hz. That way we remove the drifts present in the signal and we also remove the high frequencies which are of no interest in this case.

2. We remove the high peaks since they correspond to movement artifacts that distort the ECG signal. We apply a simple threshold: all the values higher or lower than 1000 microVolts are discarded.

3. We apply a peak detector to localize the R peaks in the ECG signal in order to cut each ECG waveform.

4. Now we align all the detected ECG waveform. Note that at this stage, the length of the ECG waveforms is not uniform. We discard the ECG shapes that have at least one point outside of 3 standard deviations of the average of all ECG waveforms.

5. Now all the ECG waveforms have more or less the same shape. The last step is to normalize the length of the ECG waveforms by resampling the part between the P and T complex, which is the one that is more dependant on the Heart Beat Rate.

The ECG we obtain that way have exactly the same length and a homogenous shape. These vectors are the ones we are going to use as features and input in our classifiers. Similarly to what was done with the EEG, we use Fisher Discriminant Analysis for the classification. In this case we have only 1 feature and 4 discriminant functions. The personal classifier approach in this case selects the best discriminant function for each subject.

The results are summarized in the following tables:

Situation	Take	TPR	FPR (EER)
Office	1	87%	13%
Office	2	88%	12%
Office	3	88%	12%

Table 3 Classification results of ECG biometric modality in the office takes.

Situation	Take	TPR	FPR (EER)
Walking	1	67%	33%
Walking	2	64%	36%

Table 4 Classification results of ECG biometric modality in the walking takes.

It is interesting to note that there is a potential in the ECG biometric modality while the subject is walking although the performance is much higher in the offices takes. There are two reasons that explain this difference. On the one hand there are much less movement artifacts in the office takes and on the other hand the office take is longer (around 3 minutes versus 1 minute).

Finally, with the recordings made with the first protocol in which the subjects were relaxed and seated we reached an EER equal to 3%. Again, the performance is remarkably higher than using the office takes, but the recording protocol is much more obtrusive and therefore not ideal or easily accepted by the users. Using the second protocol, in which the subjects are free to work or perform their daily activities, the biometric system becomes transparent for the users.

EOG

The process of measuring eye movements in different environmental contexts is called electrooculography (EOG). The EOG technique is concerned with measuring changes in electrical potential that occur when the eyes move. The EOG has been useful in a wide range of applications from the rapid eye movements measured in sleep studies to the recording of visual fixations during normal perception, visual search, perceptual illusions, and in psychopathology. Studies of reading, eye movements during real and simulated car driving, radar scanning and reading instrument dials under vibrating conditions have been some of the practical tasks examined with eye movement recordings. Eye blinks are easily recorded with EOG procedures and are particularly useful in studies of eyelid conditioning, as a control for possible eye blink contamination in EEG research, and as; : measures of fatigue, lapses in attention, and stress. There are also the periodic eye blinks that occur throughout the waking day that serve to moisten the eyeball. Still another type of eye blink is that which occurs to a sudden loud stimulus and is considered to be a component of the startle reflex. The startle eye blink is muscular and is related to activity in the muscles that close the lids of the eye. Research on the eye blink component of startle has revealed interesting findings that have implications for both attentional and emotional processes. A deeper overview can be found at (Andreassi 2007).

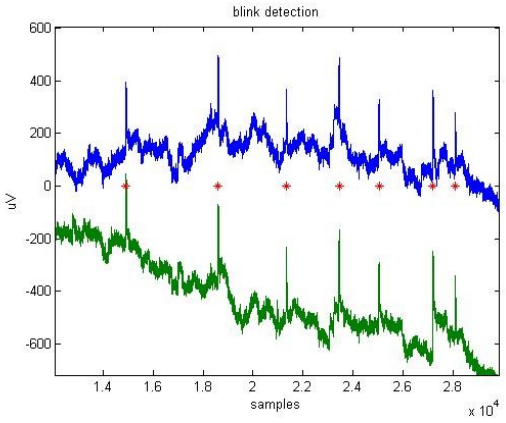

Fig. 8 EOG sample recorded by ENOBIO. The blue and green lines correspond to FP1 and FP2 respectively. The Red crosses mark the position in the signal where a blink is automatically detected by our algorithm.

A preliminary study has been performed to determine the potential of the EOG signal for authentication. The approach we used is based on blinking temporal patterns and in the shape of the blinks. This approach addresses different issues and unknowns; we do not know how dependent of time, mood, illumination, etc… the features will be and thus if the differences between subjects will be big enough to make an authentication robust trough this intra-subject changes.

The hypothesis is that the features we will use have an intra-subject variability smaller than the inter-subject variability. Of course many factors can affect the intra-subject variability such as time of the day, mood, illumination, etc…

We expect that the EOG module, even if it is not reliable enough by it self, can contribute to improve the system performance after the fusion of the different modalities.

This section explains the process followed to extract the features for the authentication process, and some preliminary results of identification and authentication using these features. The whole process can be separated in 4 main steps:

- Artifact detection and rejection
- Blink detection
- Feature extraction

- Identification/Authentication

Artifact detection and rejection

In this case, we can not apply the artifact detection described in section the artifact detection/correction, because the blinks would be treated as artifacts, and they would be removed from the signal. In this module, all the biometric information is found in the blinks, thus we want to keep them rather than removing them.

We first apply a band filter between 0.8 and 30 Hz. A threshold is then applied to the resulting signal to localize the parts of the signal over 450 and under -300 uV.

A second step is applied, but now in the frequency ….

The bad samples of the data are now detected by any of the 2 methods in any of the 2 channels. When a bad sample is detected, there is a rejection of all the data located 25 ms before and after this sample. Then we look for the remaining epochs of good data of more than 10 seconds of length. From these signals we extract the blinks, from which we extract the features. In order to detect the blinks, we developed an algorithm that detects the blinks in an automatic manner (see fig. 7).

Four different set of feature were extracted:

1. Shape of the average over all detected blinks.
2. Mean inter-blink distance.
3. Blink rate.
4. Standard deviation of the blink rate variability.

Features 2, 3 and 4 are based on blinking temporal patterns. Each feature is a number that corresponds to a component of a 3 dimension vector that is then classified. Feature 1 is classified separately and it is an 80 components vector that corresponds to the EOG time series containing the blink.

A preliminary classification was performed applying the K-Nearest neighbor algorithm. The number of subjects used for the test is 23, so the

classification rate due to random classification would be of 4.35%. Table 5 shows the results of this test.

	K-Nearest Neighbor
Blink shape	24.6%
Blinking Temporal patterns	12.5%

Table 5: Classification rate of the EOG features using LDA and K- Nearest Neighbors classifiers.

We can conclude that the blink shape and in some extent the Blinking Temporal Pattern shows some biometric potential, since the classification performance is much higher than a random classification. Although by itself it might not be a robust biometric modality, combined with other modalities it might increase the authentication performance. Moreover, with the ENOBIO system the EOG signal can be recorded at the same time that the EEG and ECG signals, making it convenient for a later fusion of those modalities.

EMG

Electromyography is the technique for measuring and recording electrical potentials that are associated with contractions of muscle fibers. The EMG is often used in the clinic to study muscular disorders. Very thin needle electrodes can be inserted into muscle tissue, and recordings can be made from limited muscle regions or even from single motor units. The EMG can also be recorded from the skin surface, because some portion of the action potentials produced in muscle fibers is transmitted to the skin. The closer the muscle tissue is to the skin surface, and the stronger the contractions, the greater will be the amount of electrical activity recorded at the surface. Most studies relating EMG to human performance deal with the activity occurring in large-muscle groups. A nice overview can be found at (Andreassi 2007).

Although being an electrophysiological measure, the muscular activity is directly related with the behavior of the body, and in particular any activity that involves contraction of the muscles, such as gait, key striking and so on.

As far as we know, there is no published work regarding a biometric system based on muscular activity. Therefore, this section describes the state of the art in recording EMG and extracting information from it, focusing on its potential application for person identification/authentication.

Electromiography (EMG) is the recording of muscular activity. It reflects not only how the muscle is, but also the work it is developing. Typical parameters that can be obtained are amplitude, mean frequency, and propagation. This last is related with the anatomy of the muscle, but also with the propagation speed of the signal.

Multi-electrode techniques offer ways to estimate better these aspects. For example, for amplitude, multisite electrode recordings have been proved to improve the quality of the amplitude analyzed. Therefore, site-specific multi-electrode arrays might provide a good way to estimate some underlying anatomical parameters of humans, which might be person-specific, or at least change slowly through time, in the same way muscular anatomy does. Therefore, there is some potential for the development of EMG recording techniques for biometry according to anatomical aspects.

A second aspect to analyze is the potential of these signals for identifying people according to behavioral aspects. This second case has already been reported for facial EMG (Cohn, 2002), contrasting it to typical camera-based systems for expression recognition, but a systematic study for different site of EMG signals is -as far as we know- lacking.

Low intrusiveness asks to process EMG signals placing electrodes in a low intrusive place. This excludes directly facial EMG because of the social importance of faces in everyday social interaction. However, there is a large amount of studies of multisite EMG for motor coordination existing (Kleissen 1998) that could be adapted. Therefore, in the same way social behaviors such as facial expressions have subject specific components that can be used for person identification, other EMG information also involving motor coordination might be. These reasons are related with the complexity of the behavior and the correlation between different parts. An example of a particularly frequent behavior that would not interfere with social interaction in an everyday environment is grasping, or tool manipulation. There are quite good techniques for analysis of these activities (Winges 2005). It would be enough to try to detect the independent components across subjects, instead of the common ones, to do person identification, instead of explaining common patterns in motor coordination.

We did a preliminary test at Starlab which is going to be explained in detail in the next part of this chapter.

6 subjects (3 males and 3 females) participated in this study. The recording device was BIOSEMI ActiveTwo. The sampling rate was set to 2048 Hz. We used 4 active electrodes placed in the forearms of the subjects (2 electrodes per forearm, see Figure 8). The reference was placed on the right wrist. The electrodes

were placed with the help of stickers and tape to make the contact more stable. We use conductive gel in all the electrodes.

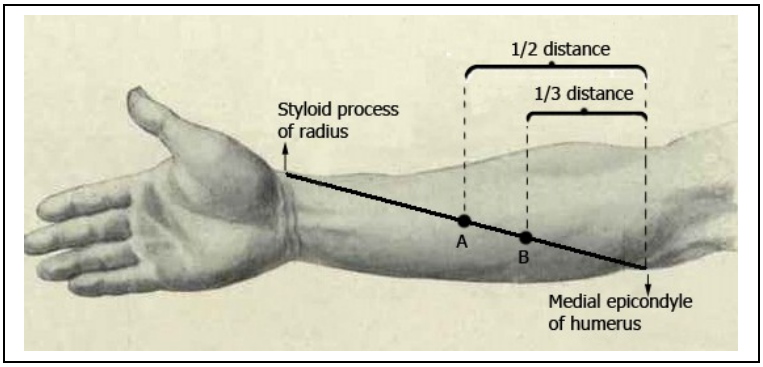

Fig. 9. This is a standard configuration to record forearm flexor (flexor carpi radialis and flexor digitorum sublimis) (Andreassi, 2007). We perform the substraction A-B in order to minimize the ECG artefacts. At the end we have two signals, one for each forearm.

The subjects were asked to type a random text on a keyboard during 2 minutes. This task was done two times in 2 different sessions. By different sessions we mean that the electrodes were remove and replaced. The interval distance between sessions was one day for 4 subjects and some hours for 2 subjects.

First of all we reference the electrode A to the electrode B, in order to minimize ECG artefacts. This setup is called bipolar configuration. This was done for each forearm, so at the end we have two signals, one for each forearm. We then applied a band pass filter between 20 Hz and 200 Hz because, although the EMG produces a wide range of frequencies, some experts agree that the maximal activity occurs at the lower end of the spectrum (Goldstein, 1972). We are now ready to extract features for each time series. Three types of features are extracted: energy averaged over number of samples, Higuchi Fractal dimension and the Fourier Transform.

Energy:

It is computed with this formula:

$$E = \frac{1}{N}\sum_{n=1}^{N} x(n)^2$$

Where N is the total number of samples and x(n) is the value of the sample n. This quantity represents the mean energy per sample. If we do not divide by the

number of samples, we would have the total energy of the signal. Just as a reminder, the total number of samples is 120 sec* 2048 Hz = 245760.

Higuchi Fractal Dimension:

It is an algorithm used to compute Fractal Dimension in real world situation, where data is sampled and so on. The algorithm we use is the one used in the work (Arjunan, 2007). For a detailed description see (Higuchi, 1988)

Fourier Transform

We compute the power spectrum density using Welch method (Welch P.D , 1967).

Once we have the feature extracted we are ready to present some preliminary results.

In Error: Reference source not found we can see the scatter plot of the energy of the right forearm versus the energy of the left one. We can see that there is a clustering tendency. In fact we can visually group the 4 takes of the six classes in all cases except in one (the blue round would be considered as belonging to the green class). The classification rate is thus equal to 23/24=0.9583.

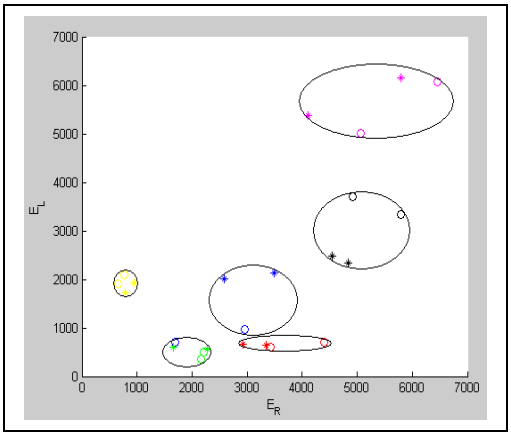

Fig. 10. Energy of right forearm versus Energy of the left one. The different colors represent different subjects and the o represents the 2 takes of the first session and the * represent the two takes of the second session.

Regarding the spectrum, we can see in Figure 10 which corresponds to the left forearm, that it is easy to visually discriminate between subjects, except maybe for the blue, which is similar to the yellow and to the red. In fact for the blue one, the inter subject variability is big compared to the intra subject variability. The

spectrum of the right forearm is more ‘mixed’ than the one for the left (see Figure 10 and 11).

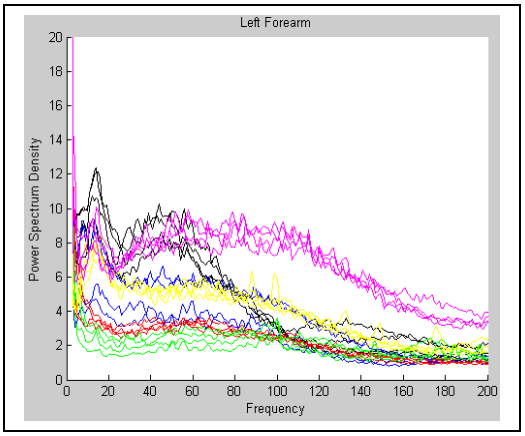

Fig 11 Power Spectrum density for the 4 takes of each subject (Left Forearm). Each subject is represented by a color.

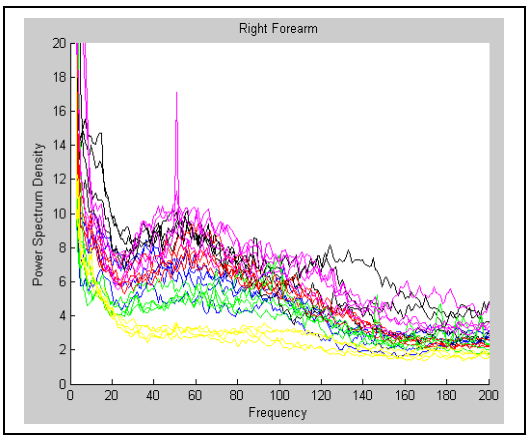

Fig 12 Power Spectrum density for the 4 takes of each subject (Right Forearm). Each subject is represented by a color.

Even thought we do not have a significant number of subjects nor takes, the results show that there is a discriminative potential in EMG based features. Probably by fusing the results from the different features we are able to correctly classify all the takes for the same subject. This work is still to be done in a more systematic way, and we might in the future record more EMG data from a larger data set.

Technology Trends and Opportunities

Much of the current research in electrophysiological biometrics is naturally focused on improving performance, robustness and comfort for the user. It is often pitched as an alternative to existing technologies such as finger-print recognition, iris recognition and voice recognition. This assumes that the application space is the same and that what we offer is "more" security, for any given application, such as secure access.

This, however, is not the case. Electrophysiological biometry is fundamentally different in that it brings added value to existing security applications and is, perhaps more importantly, closely linked to emerging technologies that will generate new opportunities and requirements.

To quickly touch on the first point, what is the added value?

Essentially it is the ability to provide information on the user's physiological status while authenticating that user. This information can then be used to determine affective or emotional state which may have implications for the security of the system. For example, if a user is unusually stressed when accessing the system it may notify security and request a face-to-face follow up to ensure all is well. There are evidences that electrophysiological signals are related with emotions. For instance, "exotic" physiological activities such as gastric myoelectrical activity have been reliably assessed to be related with certain emotions (Vianna 2006). Regarding ECG, the classification of 4 basic emotions has already been achieved based on detecting the physiological correlates of them on ECG and respiration data (Rainville 2006). This article uses respiration and ECG signals to discriminate 4 basic emotions, according to the subjective report of them. Since it is possible to extract respiration form ECG, it might be possible to detect these 4 emotions using only an ECG lead. There are also some indications showing that indirect measures of emotions can be obtained from EEG data. For example, phase synchronisation between different cortical areas (Costa, 2006) seems to relate closely to emotional intensity, and to be different for different emotional reactions. Non-linear indexes as Kolmogorov complexity might as well reflex emotionally significant activity (Ljubomir 1997).

Looking at emerging technologies we can see that not only is there added value for existing security applications but there is a growing market in applications that rely on electrophysiological signals to carry out their primary task. What this means is that these users are already wearing a sensor system capable of recording electrophysiological signals. This is a game changing shift in the field as it addresses one of the most serious shortcomings of electrophysiological biometry;

the need to wear or touch electrodes capable of recording the signals needed to extract the relevant features.

Brain Computer Interfaces

BCIs are beginning to make the jump from the research lab to commercial applications and will soon arrive in your living room.

There are many examples of BCIs being used to control smart homes (Guger 2009) and mobility devices for the disabled such as the Toyota wheelchair controlled by a BCI[1]. Regardless of the type of BCI, be it Synchronous Motor Cortex activation, Steady State Evoked Potentials or any other, we will have access to the raw EEG signal while the device is being used. Not only can we authenticate the user at the beginning of a session but we can continuously authenticate them. This can be transparent to the user and extremely difficult to bypass. As BCIs become more user friendly and comfortable their use will only increase (Riera 2008b). In recent months we have also seen the emergence of cheap commercial BCIs targeted at the game and toy markets. These devices may soon be standard equipment providing access to your brain waves and their biometric potential.

Brain Computer Interfaces

As far as we know, the approach we describe here has never been used for authentication purposes. In the next lines we will describe a scenario in which a subject, by loading and controlling a Brain Computer Interface (BCI), will be authenticated and will successfully unlock a computer in order to access its information. First of all, we provide a definition of a BCI: A Brain Computer Interface is a system that translates brain activity into control actions to be performed by artificial effectors, in our case, a computer. There are many types of BCI's and they can be classified depending on many factors, such as level of intrusiveness, based on EEG (endogenous) or based on Event Related Potentials ERP (exogenous), based on motor imagery or based in more complex cognitive tasks, etc…One of the problems of BCI systems is the need for personalization. That is, the system needs to be tuned for each person in order to improve performance. While this is a disadvantage for BCI applications, we can use it as an asset for biometry.

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1 **Real-time control of wheelchairs with brain waves** **http://www.riken.jp/engn/r-world/info/release/press/2009/090629/index.html** Accessed October 26th 2009

In our model, we will introduce a simple motor cortex based BCI applied to biometric authentication. Most of the BCI's need a training phase, in which the subject is asked to perform certain mental imagery tasks according to some cues provided by a screen. For instance, in our system the subject will first of all decide which 2 motor imagery tasks he/she wants to perform in order to code 2 actions: left and right (the cues would be an arrow pointing right and an arrow pointing left). The subject could choose for instance left hand for left action and right hand for right action but many more combinations could be used choosing imagery tasks from the next list:

- Right hand
- Left Hand
- Right foot
- Left foot
- Both hands
- Both feet
- Tongue

In total, we have 42 possible combinations. Each subject will choose his own imagery tasks, and he/she would keep it for himself, in the sense that only he/she should know his/her imagery tasks. Once the subject has performed the training which can be considered as the enrolment into the biometric system, all the EEG recorded data will be used to select the best combination of features, classifiers and electrodes for each particular subject in order to maximize the classification rate of his/her training set.

Now the subject is ready to use the BCI in authentication mode. In order to unlock the computer, the subject will first of all claim his identity in order for the system to load his personal BCI (with the optimal combination of features, classifiers and electrodes for that particular subject). Then he/she will have to control a virtual locker in order to provide a password only known by him/her. In order to input the digits of the password, the subject will need to move the cursor to the corresponding number by performing motor imagery tasks (just as during the enrolment phase). If he/she accomplishes to do so in a limited amount of time, then the computer will be unlocked, and the subject authenticated.

There are 2 levels of security: the password and the control of the BCI. The biometry involves two aspects: on the one hand, the features, classifiers and electrodes locations are personalized, on the other hand, only the subject will know what imaginary movements he/she needs to do (hands, feet or tongue as explained before).

Telepresence Systems

As technology advances and environmental and political pressure increase we are beginning to see the first viable telepresence systems such as the one offered by Cisco[2]. These systems show huge potential for the reduction of business travel and the corresponding environmental impact.

However these systems are not just about video conferencing, research on Presence, VR and advanced interfaces is paving the way for fully immersive systems where not only will your image and voice be transmitted but also your physiological and emotional state. This augmented representation of the user can compensate for the lack of the personal multi-modal interaction that we are used to in daily life.

It can also address another issue associated with digitally reconstructed avatars as representatives; that of trust. If the person that claims to be speaking to you is authenticated by their own heart or brain signals we can reintroduce some sense of a flesh and blood person.

Vision for the Future and Risks

In previous chapters we have discussed emerging technologies and trends that will have a profound influence on electrophysiological biometrics. One of the more important is BCI and from our point of view, the future regarding electrophysiological biometrics is very much related with the future of the BCI technologies. There are many different ways to classify the various approaches to BCI but level of invasiveness is one of the most fundamental.

There are essentially 3 levels of invasiveness:

- Non-invasive BCI typically using external EEG electrodes.

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2 **Cisco Telepresence Solution**
http://www.cisco.com/en/US/netsol/ns669/networking_solutions_solution_segment_home.html Accessed October 26th 2009

- BCI based on electrocorticogram (ECoG) which is obviously more invasive, since now the electrodes are placed directly on the surface of the brain (cortex) , having previously removed a piece of the skull.

- And the most invasive BCI approach of all where the electrodes are placed inside the brain (deep brain electrodes), by means of long needles with the recording part in the tip of the needle.

In any BCI the key to success is being able to distinguish your signal or feature of interest from the background noise (everything else that is going on). The versatility of the BCI depends on the number of separate states that can be classified from that signal. In many cases, such as motor cortex BCIs (Wang 2006), this depends on being able to record a clean, well localized signals corresponding to well defined activation patterns. This is obviously easier to do on the cortical surface itself (ECoG) than on the surface of the scalp (EEG).

So here we have two contrary requirement drivers, on the one hand performance improvement pushes us towards invasive techniques while on the other, user acceptance and comfort push us towards non-invasive techniques. Obviously opening your skull in order to install a BCI is unacceptably aggressive and so we try to develop non-invasive EEG systems that apply ever more advanced signal processing and machine learning based classification techniques.

Looking to the future however we can ask, will this always be the case?

Recent work (Song 2009) has shown significant improvement in invasive ECoG devices. These systems show great promise and may soon be seen as an appropriate response to certain circumstances. Pace makers and cochlear implants have become standard and the procedure for implanting them routine. There is every reason to expect that the same will be true of cortical implants if the benefits justify the risk. A reliable and versatile BCI that allows a paralyzed patient to interact more fully with their environment may be sufficient motivation.

In the future, both the electrode size and the procedure to implant them will surely improve and thus probably making the use of deep brain electrodes and implanted ones more common than nowadays. The electrodes of the future will be very small, will consume very few energy (they could even be powered by the subject’s body movements or temperature changes) and of course wireless.

So we see that even in the most invasive case there is reason to expect an increase in uptake of these technologies and therefore an increase in the number of users that may take advantage of electrophysiological biometrics.

While there are many advantages to “always on” authentication and many advantages to having access to background physiological information we should not forget that for most normal use scenarios, where privacy and anonymity are valued, this may not be appropriate.

These issues must be very carefully studied and their implications clearly understood before any such system becomes widely implemented. Ensuring the privacy of Personal Health Records is a major concern for the main players in this arena as has been seen with the launch of Google Health and MS Health-Vault. These concerns will surely be raised for any system that has direct access to the physiological signals of a user.

Conclusion

Although the electrophysiological biometry is still in his youth and any commercially available device does not exist yet, this approach to biometric is very interesting for several reasons.

First of all, the possibility to perform a continuous authentication is very attractive because that way the subject does not need to follow any particular protocol in order to get authenticated, making the system transparent for the user. Of course in order to minimize the obtrusiveness, the recording device should be wearable and wireless. Moreover, such a device should be as small and comfortable to wear as possible. There are devices nowadays that fulfill these requirements, but certainly in the future, the miniaturization of both the electrodes and the electronic compounds will make those systems much less obtrusive. The possibility of implanted electrodes is also very attractive but in this case a lot of ethical issues arise: do we want always on systems? How will the privacy and anonymity of the data be handled? Will the society be going towards a ‘big brother’ type of society?

A second interesting feature of the electrophysiological biometry systems is their universality, at least for ECG and EEG. We can affirm that every living person has a beating heart and a brain that produces electrical signals. Some other standard biometric features are not universal or hard to collect in certain conditions. For instance for voice recognition, the subject needs to be able to speak, and even if he/she can speak but suffers from aphonia the biometric test would probably fail. The same applies to fingerprint recognition in which the fingerprint collection might fail if the finger skin of the subject is dry, or even if a small wound is present in his/her finger tip.

The possibility to extract more information besides the identity of the subject is a very interesting added value to the electrophysiological biometry. There are evidences that EEG, ECG and EMG can provide information related to the

emotional state of the subject. This can be very useful in order to decide if a subject is in the proper conditions to fulfill his/her work. That becomes obviously interesting if the task of the subject requires a high concentration level and is potentially dangerous such as truck driving, nuclear plan controller or traffic air controller. Also in the future, the telepresence and virtual reality environments would become more and more used. In this field, the electrophysiological biometry can authenticate the avatars continuously, so we could be sure we are speaking with the right person in the virtual world and thus being more secure if we are sharing private and/or confidential information. We could also get access to the emotional information of the avatars, something related with the field of augmented reality, where humans can access information that are hidden to the 'common' senses. This could have many applications in the field of virtual reality storytelling (reference?) and virtual reality entertainment.

Many studies have been done with EEG and ECG. The challenge now is to take these systems outside the laboratories and study if the performance is maintained in real world applications where more artifacts are likely to appear. At least at this stage we can claim that the results are promising for these two modalities.

Regarding EMG, the results are promising as well, but very preliminary since a study with much more subjects should be done in order to extract deeper conclusions. It is interesting to note that this study is the first in which EMG is used a biometric feature, as far as the authors know.

Finally EOG has also been tested as a biometric feature, but in this case the results are poor. There is some biometric potential in EOG, but the performance does not match other biometric modalities. Probably the use of improved classifiers techniques, the search for new features in EOG, and the use of electrodes below the eyes (and in the sides of the eyes) to have access to vertical and horizontal movement separately and also to blinks would improve the performance, but this study is still to be done.

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Appendix E

Identity and Trust in Virtual Environments

This enclosed work that follows was published as a Conference Paper in the proceedings of the "Presence Technologies (RAVE'10)" organised in Barcelona, Spain, the 3rd of March 2010 . For complete reference please see Riera and Dunne [35].

RAVE-10 Abstract

Barcelona, March 4th 2009

Identity and Trust in Virtual Environments

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[1]Starlab Barcelona S.L.

Abstract

1. Introduction.
When interacting with other people in virtual environments we are usually interacting with an avatar that we take on trust to represent a particular person. The fact that the avatar may have virtually any appearance possible and that the same avatar may be controlled by different people at different times raises some interesting questions on why we should trust what we see.
With this in mind we have developed a biometric system that authenticates a user using its own heart beat and brain waves. These signals from a living human may provide a route towards improving the sense of interacting with another person.
In parallel we have developed a system that makes use of specific BCI tasks as a means of authentication.
In both cases our work is built on our own ENOBIO wearable electrophysiological recording device and both can be implemented in parallel and continually.

2. A clear statement of the problem specifically covered by the study, and the current state of the art.
It has been proven that electrophysiological signals, such as EEG [1, 2, 3, 4, 5, 6, 7] and ECG [8, 9, 10, 11, 12], are unique and robust enough to be used for biometric purposes. They also show some advantages over other traditional biometric systems, such as voice or fingerprint recognition, including universality [13]. EEG and ECG can also be recorded simultaneously with the ENOBIO wearable amplifier and the results of both biometric modalities can be fused, improving the performance of the system.

From our point of view, the two major problems related with electrophysiological biometrics are the user acceptance and the movement artifacts, including EOG artifacts, which affect the quality of the signal. By using the ENOBIO amplifier, which is wearable, wireless, can work in dry mode and it is automatically calibrated, the former problem is solved. Regarding the artifacts, two solutions have been explored: the use of an authentication protocol, where the subject is asked to not move during the recording time and the use of an artifact correction algorithm.

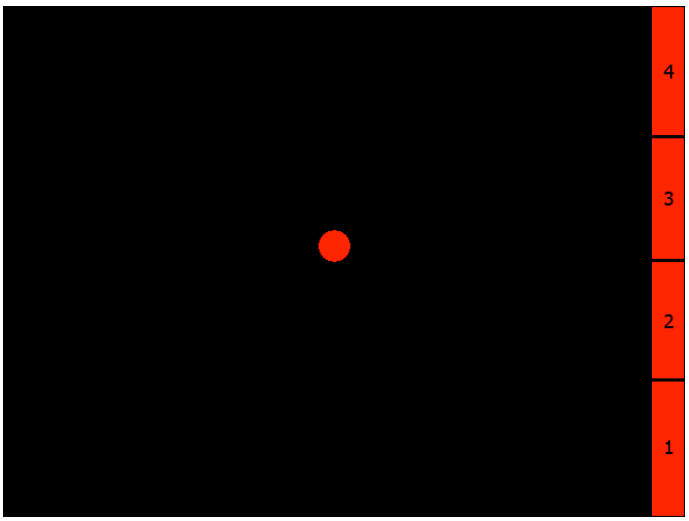
In addition to the use of EEG and ECG for biometric purposes, we also used the control of a BCI system for authentication purposes. In this case, rather than being a passive biometric system, we are dealing with an active system in the sense that the user needs to perform a specific task in order to be authenticated. As far as we know, it is the first time that a BCI system has been used for biometric purposes.

Our BCI system uses a simple motor cortex desynchronization based BCI applied to biometric authentication. Most of the BCI's need a training phase, in which the subject is asked to perform certain mental imagery tasks according to some cues provided by a screen. For instance, in our system the subject will first of all decide which 2 motor imagery tasks he wants to perform in order to code 2 actions: left and right (the cues would be an arrow pointing right and an arrow pointing left). The subject could choose for instance left hand for left action and right hand for right action but many more combinations could be used choosing imagery tasks from the next list:

- Right hand
- Left Hand
- Right foot
- Left foot
- Both hands
- Both feet
- Tongue

In total, we have 42 possible combinations. Each subject will choose his own imagery tasks, and he/she would keep it for himself, in the sense that only he/she should know his/her imagery tasks. Once the subject has performed the training which can be considered as the enrolment into the biometric system, all the EEG recorded data will be used to select the best combination of features, classifiers and electrodes for each particular subject in order to maximize the classification rate of his/her training set.

Now the subject is ready to use the BCI in authentication mode. In order to be authenticated, the subject will first of all claim his identity in order for the system to load his personal BCI (with the optimal combination of features, classifiers and electrodes for that particular subject). Then the user will have to control the vertical movement of a moving virtual ball in order to hit some specific targets in a specific order (see figure below). The control will be done by performing motor imagery movements (just as in the enrolment phase). Each target represents a number. That is the way the subject will input the password in the system. For instance if the password is 1234, the subject needs to hit the 1st target, then the 2nd, the 3rd and the 4th in that specific order. Each time a wrong number is hit then the whole password needs to be input again. If the user accomplishes to do so in a limited amount of time, then the subject will be authenticated.



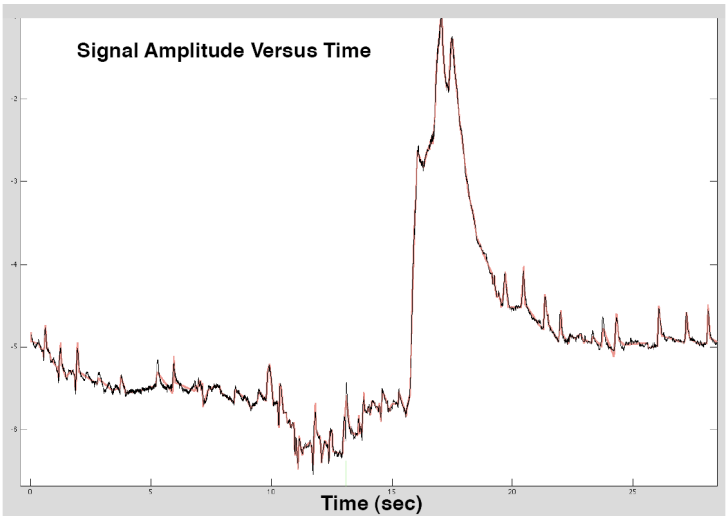
Screenshot of the BCI based biometric system. The 4 targets in the left represent the numbers 1, 2, 3 and 4. The subject has to hit those targets in order to input his/her password. The ball has a constant x-speed. The subject controls the vertical movement of the ball by performing mental imagery movements.

There are 2 levels of security: the password and the control of the BCI. The biometry involves two aspects: on the one hand, the features, classifiers and electrodes locations are personalized, on the other hand, only the subject will know what imaginary movements he/she needs to perform (hands, feet or tongue as explained before).

3. A section beginning with "Here we show" giving the main result, explaining what new knowledge has been generated.

As explained in the previous section, we have tested two approaches regarding the electrophysiological biometric system. The best results are obtained using a strict protocol while the data is being recorded. The subject is asked not to move, stay relaxed comfortably seated and to close his/her eyes. That way we minimize the movement artifacts. The data recording time is 1 minute. For EEG, we reach an Equal Error Rate (EER) = 20.8% and for ECG the EER = 2.1%.

The problem with this approach is that it is much more obtrusive than having no protocol at all. In other words, the users will accept much more a transparent biometric system than one that requires a specific protocol that will make him/her lose time in order to be authenticated. That is why we have also focused in an approach that does not require any specific protocol. The subject is free to move and to perform any activity, while the data is being recorded. In order to process the data and to extract the relevant features, we have developed an artifact correction algorithm that cleans the movement artifacts from the signal. This method is based on fitting a curve based on 3 parameters (called fitting parameters) to the recorded signal, and then subtracts the curve to the original signal. We can see in the following figure that both the blink artifacts (small peaks) and the big drifts (visible in the middle of the figure) are well characterized.



Red line is the artifact estimation that will be subtracted to the raw signal.

Using this approach we reach an EER = 25.6% for EEG and an EER = 12.3% for ECG. Although the performance is a bit lower in this case, we consider that the advantages of using this approach are very interesting, since it makes the system transparent for the user.

Regarding the performance of the BCI biometric system, we are still in a very early stage of the research and our intention here is to demonstrate the proof of concept.

4. A section explaining what the main result reveals in direct comparison to what was thought to be the case previously, or how the main result adds to previous knowledge.

We have improved our electrophysiological biometric system by making it transparent for the user. The artifact correction we have implemented allows the subject to wear ENOBIO and perform his daily activities while being authenticated continuously. The user needs no longer to follow a strict protocol in order to minimize the movement artifacts. This is a great advantage in the sense that the subject does not need to lose any time for the authentication procedure to take place.

Besides this achievement, we have tested a very new approach to biometrics by introducing the control of a BCI as a biometric test. From our point of view, the BCI system will become more ubiquitous and even if it seems a futuristic approach in the present, in the future that might be a very natural way to interact with computers. In this scenario, the use of a BCI for authentication purposes might become as normal as the fingerprint authentication systems that are present in many laptops nowadays.

5. A section putting the results into a more general context, and the implications for further research.

We have demonstrated proof of concept for electrophysiological biometrics, including the use of a BCI. We believe that apart from authentication this technology will become more important over time for two reasons:

1. It opens the way to providing real time information on the affective state of users.
2. As BCIs become more ubiquitous the system needed will already be in place and will be a natural part of virtual interaction.

The use of electrophysiological signals in virtual environments is a very interesting way to extract information of the avatars that characterize human users, but it is also interesting in order to control the movement of the avatars, by means for instance of a BCI system.

In this scope, the use of the previously described system in such a virtual environment will become very natural. First of all, the system is wearable, wireless and very easy to place. It can be used to authenticate the avatars, increasing the trust in virtual interactions. It can also be used as a mean to perceive augmented reality feature from the subject. Using the same system (which records EEG and ECG) we could extract feature that correlates with the affective state of the users, such as stress, relax, concentration, fear, etc…[15, 16, 17]. This information could be perceived by other users in the virtual environment by displaying an aura around the avatar which colors would change depending on his/her emotional state. Moreover, this information can also by used by the virtual environment scenario or by the computer controlled avatars in order to build a story that will fit the emotional changes of the human user [14].

Finally, the use of the BCI for authentication purposes perfectly fits in a virtual environment where the movement of the avatar is controlled by a BCI. In that case, our system will only provide extra information about the identity of the subject.

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Appendix F

Fusion operators for multi-modal biometric authentication based on physiological signals

This enclosed work that follows was published as a Conference Paper in the proceedings of the "Fuzzy Systems (FUZZ), 2010 IEEE International Conference" organised in Barcelona on July 2010. For complete reference please see Soria-Frisch et al. [36].

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Fusion Operators For Multi-modal Biometric Authentication Based On Physiological Signals

Aureli Soria-Frisch, *Member IEEE,* Alejandro Riera, and Stephen Dunne

***Abstract*— The most basic operators, like the sum and the product, have been used for data fusion in many application fields together with ordinal operators and the majority voting operator since the early stages of research. These application fields include biometrics, which constitutes the focus of the paper presented herein. All these operators have evolved into more advanced ones, particularly through the results of soft-computing and fuzzy operator research. However, these advances in state of the art have not been transfered to the different application fields. The presented work provides a comparison of different soft data fusion operators in a biometric application. Hence we analyze the performance of their application in a multimodal system, which takes into account two modalities based on physiological signals, electroencephalogram (EEG) and electrocardiogram (ECG). The analysis is done by evaluating the performance of five operators on a 29 subject database. The performance improvement due to the application of a soft data fusion stage is evaluated and demonstrated.**

***Index Terms*— Soft data fusion, fuzzy aggregation operators, biometry, multi-modal biometrics, physiological-based biometrics.**

I. Introduction

Data fusion and data integration are terms commonly confused. Both are related to the employment of multi-sensory data in data analysis frameworks like those used in biometrics. In this context different sensory or processing units are capable of generating data related to different biometric traits. The so-called sensory gap, which denotes the limitation of a sensor unit to represent just one particular aspect of reality, is overcome by extending the number of sensors, and consequently, the associated facets of reality. In the case of biometrics the sensory gap can be extended to different data analysis modules that may work with a single sensor device, e.g. camera, but that extract different biometric cues, e.g. gait, face. The simultaneous inclusion of these different sensors or the results of their associated analysis modules in a biometric system and, particularly, of the generated data in the data analysis system is denoted as data integration. This is often denoted in the biometry literature as a multi-modal biometric system [1]. Furthermore the transformation of the multimodal classification results into one representational form [2] is denoted as multimodal biometric fusion. The application of this concept in a biometric system is expected to improve the performance of the overall biometry recognition system [3][4].

The simplest way of fusing data is putting them in a common reference system, whereby the resulting data dimensionality is the sum of the individual ones, e.g. [5][6]. In this way a general purpose processing or classification algorithm can be used in the larger dimensional feature space. However this configuration results in the disadvantage that pattern recognition systems present more counterintuitive behaviors in large feature spaces than in smaller ones, known as the curse of dimensionality [7]. Beyond this fact, some studies emphasize the importance of developing special data fusion algorithms for applications where data fusion is involved [8] in order to take full advantage of this processing stage. That study claims that the most important steps when developing fusion algorithms are: to acquire consistent data sets, co-register them, and develop appropriate data fusion techniques. In contrast to this statement several works make use of classical fusion operators, e.g. [9][4], or general purpose pattern recognition techniques, e.g. [10], for fusion. This occurs in spite of several existing reviews on fuzzy fusion operators [11][12][13]. We undertake a comparison of fusion operators furthering these three reference works w.r.t. the applicability of the results. Hence we do not attain neither a theoretical nor a benchmark problem based comparison, but a comparison within a particular application domain, i.e. biometry. Therefore we compare five different soft data operators for the fusion of multi-modal data within a biometric authentication system. In particular one of the novelties of the work is the inclusion of power means and uni-norms in the performance evaluation with data of a particular application domain.

The biometric system being developed is devoted to authentication in an ambient intelligence environment. Hence, it presents the feature of taking into account biometric authentication when the user being authenticated performs different types of activities. Therefore the number, nature, and confidence level of the extracted biometric modalities depend on the type of activity being performed. A similar authentication system to the one analyzed herein, which uses two physiological signals for person authentication, has been presented in [14]. However that work dealt with the performance tuning of the individual modalities, i.e. the performance of the classification on the electroencephalogram (EEG) and electrocardiogram (ECG) signals. Moreover their fusion was realized through an average operator. We extend the number of evaluated fusion operators in the research works. Lastly the data acquisition protocol for the data

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analyzed in [14] fixed laboratory conditions. On the contrary we analyze data acquired in a real-world office scenario.

As a general goal, the fusion scheme to be applied has to improve the overall robustness of the biometric authentication. In this case we attain the selection of a fusion operator with the optimal performance in absolute terms. Furthermore we attain the robustness analysis of the operators with respect to a subject change. Therefore we would like to know if the performance level remains similar in the following two cases: if we use a fusion operator with some particular parameter for all subjects or if we use a different fusion operator for each subject. Moreover we attain the selection of the optimal operator within these conditions. For this purpose we take into account an EEG-ECG data set and compare the performance of five soft data fusion operators in terms of Receiver Operating Curves (ROC), and the more synthetic Area Under the Curve (AUC). Here the numerical goal is to maximize the AUC value [15]. As in this previous work, we compare the operator performance when dealing with fusion at the classification level.

This communication follows the following structure. Section II presents the theoretical background of the operators that are analyzed in the following sections. The evaluation methodology, further detailing the application domain, is described in Sec. III. While the results are given in Sec. IV, the inferred conclusions and projective work can be found in Sec. V.

II. Analyzed Fusion Operators

The most basic operators developed in mathematics are the sum and the product. These operators have been used together with some other lightly evolved ones like the ordinal operators maximum, median and minimum and the majority voting operator in data fusion from an early stage of research [9]. They are still used in schemes including data fusion methodologies together with light modifications and further simple ones like the average operator [16][17]. However all of these operators are just the starting point from which more advanced fusion operators have evolved, particularly in the field of soft-computing and fuzzy operator research [2]. Different families of operators were already theoretically compared in [11], i.e. T- and S-norms, means (f-mean, OWA, Choquet Fuzzy Integral), MYCIN operators, the Dempster orthogonal sum, possibility fusion operators, Bayesian based fusion operators, and symmetrical sums. Furthermore [12] makes a comparison of fuzzy aggregation operators versus non-fuzzy ones. It compares, on the one hand the weighted majority voting, the minimum, the maximum, the average, the product, and the Naïve-Bayes operators, and on the other hand, the fuzzy integral and so-called decision templates in six benchmark pattern recognition problems. The authors finally state that fuzzy fusion outperforms non-fuzzy operators in these six problems. To the best of our knowledge the work in [13] undertook the most recent review on fuzzy aggregation from a theoretical point of view. Although not being so complete as [11], it includes some of the most recent developments in the field, e.g. uni-norms and absorbing norms, together with interesting aspects on the topic.

Following the aforementioned works we undertake a comparison of five soft data fusion operators. Soft data fusion is a framework that attains structuring the different fusion operators presented heretofore [2]. In the framework operators are placed in a bi-dimensional map that takes into account the so-called softness degree of the operator and the family to which it belongs due to the generalization relationship with other ones (see Fig. 1). The fusion operators taken into account in this work have been selected following two criteria. First, they belong to different operator families and present different degrees of softness. Moreover they have been selected after a preliminary analysis of the level curves of several operators (see Figs. 2-6). This analysis has been used for assessing their diversity, which has been the second selection criteria.

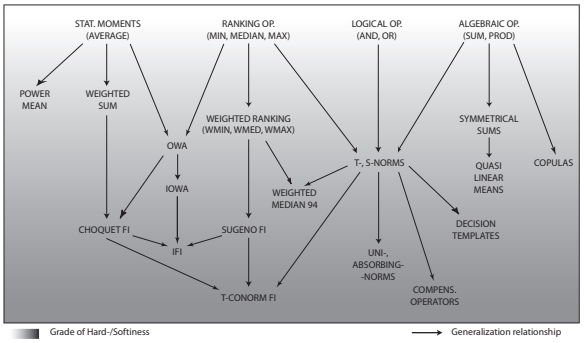

Fig. 1. Evolution of fusion operators from the basic ones into different operator families structured within the soft data fusion framework. IOWA: Induced OWA. IFI: Induced Fuzzy Integral. Extended from [2].

A. Power or Generalized Mean

The mean is one of the most well-know fusion operators. It is used in statistics for finding the central location of a probability distribution. This is attained through the application of the arithmetic mean. There are other mean operators like the geometric mean or the harmonic mean. Moreover a parametric generalization of all these expressions has been proposed [18], which is known as the power or generalized mean. It presents the following expression

$$z = \left(\frac{1}{n}\sum_{i=1}^{n} x_i^m\right)^{1/m}, \tag{1}$$

whose value depends on the real-valued parameter m, e.g. for $m = 1$ results in the arithmetic mean and for $m = 2$ is denoted as the quadratic mean (see Fig. 2).

B. Yager S-norm

T- and S-norms, whose fundamentals were introduced in [19], are aggregation operators related with the concept of

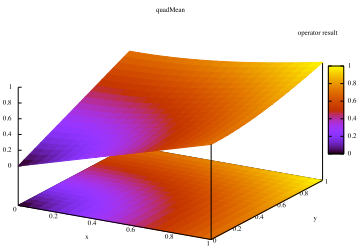

Fig. 2. Level curve of the quadratic mean, i.e. power mean for $m = 2$.

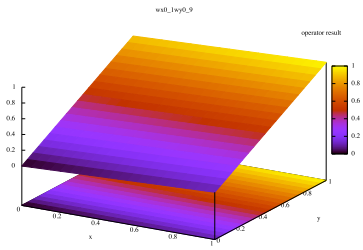

Fig. 4. Level curve of the weighted sum for $w_1 = 0.1$ and $w_2 = 0.9$.

statistical metrical spaces [20]. T- and S-norms were adopted in fuzzy systems for operating with fuzzy membership functions [21]. The Yager S-norm has been selected herein after a preliminary study taking the diversity of operators to be analyzed into consideration. This S-norm presents the following expression and level curve (see Fig. 3):

$$z = \min\{1, (x_1^p + x_2^p)^{1/p}\}, \tag{2}$$

where $p \in [0, \infty]$.

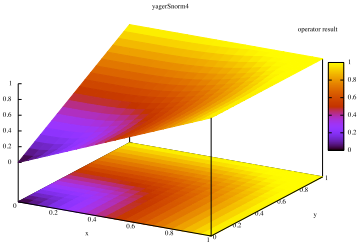

Fig. 3. Level curve of the Yager S-norm for $p = 4$.

C. Weighted Sum

The weighted sum is an operator used in different application domains, e.g. descriptive statistics, neural networks. It is a further generalization of the arithmetic mean. In this case the generalization is done by weighting the input values, i.e.

$$z = \sum_{i=1}^{n} w_i x_i. \tag{3}$$

Usually the sum of the weights is normalized to sum to 1, which ensures that we are working in the unit hypercube (see Fig. 4).

D. Uninorm Based On Yager Norms

Uni-norms were introduced in [22]. Uni-norms generalize T- and S-norms by introducing an arbitrary neutral element denoted as e [13] defined in $[0, 1]$ such that $U(x, e) = x$. There exists a mathematical expression to map T- and S-norms into Uni-norms. The mapping $U \rightarrow T, S$ holds for the unit hypercube, whereas $T, S \rightarrow U$, only for the spaces $[0, e]^2$ and $[e, 1]^2$. In the other subspaces the uni-norm shows a compensating behavior, i.e. the result value is between minimum and maximum. There is a particular type of uni-norms denoted as representable among which we can find the operators used in well-known fusion paradigms of expert systems, like MYCIN and PROSPECTOR [23]. The work in [24] presents the concept of absorbing norm, which in some sense is dual to this of uni-norm. They present a so-called absorbing element a, whereby $A(x, a) = a$.

One can see uni-norms and absorbing-norms as two different ways of combining T- and S-norms in the unit hypercube. Thus in the uni-norms the subspace $[0, e] \times [0, e]$ is occupied by a T-norm, whereas $[e, 1] \times [e, 1]$ by a S-norm. In the remaining two sub-spaces there is a compensatory operator, although this is not a condition of the operator (i.e. the only condition is that the resulting operator must be commutative and associative). Moreover these two quadrants have to be filled by compromise operators like means or min/max itself. In the results given in Sec. IV we have selected a uni-norm based on the Yager T- and S-norms, and on the arithmetic mean in the U-quadrant. The resulting uni-norm presents the following level curve (see Fig. 5).

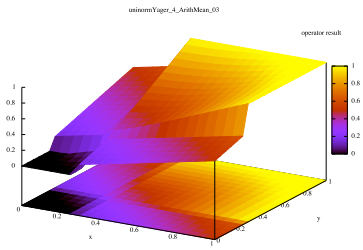

Fig. 5. Level curve of a uni-norm (for $e = 0.3$) based on Yager T-, and S-norm (with $p = 4$), and the arithmetic mean.

E. Ordered Weighted Averaging

A generalization of the average, where the weighting is established after sorting the input data, was proposed in [25] and denoted as Ordered Weighted Averaging (OWA). The OWA presents the following expression:

$$z = \sum_{i=1}^{n} w_{(i)} x_{(i)}, \tag{4}$$

where $w_{(i)}$ are the weights of the operator. The bracketed subindices state for a sorting operation that is applied on x_i before aggregating their values, e.g. (1) state for the larger x_i, (n) for the lowest one. The operator definition results in a unique weighting set, but that is applied to different channels on each canonical region of the unit hypercube [2]. This can be observed in its level curve (see Fig. 6).

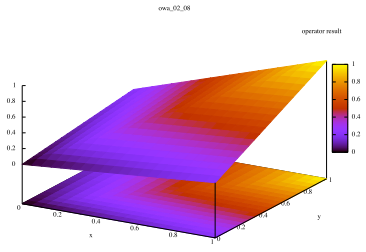

Fig. 6. Level curve of the OWA for $w_{(1)} = 0.2$ and $w_{(2)} = 0.8$.

III. Application Domain and Methodology

The operators mentioned in the former section have been tested with a data set acquired within an ambient intelligence facility. Up to 29 subjects go through a data acquisition protocol within two different scenarios denoted as workplace and office. In the first one the subject walks around the workplace, whereas in the second one, a seated subject realizes different office related activities, e.g. answering the phone, watching a video, typing a document on the computer. As a consequence different modalities are applied to the different activities, i.e. a modality like gait can not be extracted when the subject is sitting. For a preliminary analysis we have selected the activity of watching a video, where the subjects are authenticated herein through the Electroencephalogram (EEG) and Electrocardiogram (ECG) modalities [14].

The tests are done in order to attain 3 goals. First the optimal parameter set of the operators mentioned in Sec. II for each subject will be selected. Second, the optimal fusion operator for each subject will be established. This will be achieved by comparing the performance of the operators when being parameterized with their optimal parameter set. Lastly, the robustness with respect to a change in the subject of the operators will be analyzed.

Given the ground truth of subject authentication, the validation criteria is the Area Under the Curve (AUC). The AUC is defined as the area covered by the Receiver Operating Curve, which relates the True Positive Rate (TPR) and the False Positive Rate (FPR). The AUC can be computed as the integral value of the TPR w.r.t. FPR. For a complete review of the utilization of the ROC in performance assessment the reader is referred to [26]. The optimal parameter set for each operator is computed through an extensive search over the parameter space. Therefore the AUC of the ROC for each parameter set of the operator being optimized is computed. The parameter set delivering a maximal AUC is select as the optimal one for the corresponding operator.

When characterizing the robustness of a particular fusion operator we will use the average and the variance of the AUC over subjects. Then we take as the most robust parameter the one with the maximal value of minimal expected performance over parameter values. Here the minimal expected performance over parameter values is computed as the the mean value of the average AUC over subjects minus the variance of the AUC over subjects. The most robust parameter is this delivering a maximal value in this difference.

IV. Performance Evaluation on Preliminary Results

As described in the former section, the optimal parameter set has been computed for each of the fusion operators being evaluated. As mentioned in the former section this is achieved by an extensive search in the parameter space. An example of the results attained in such a procedure is shown in Fig. 7.

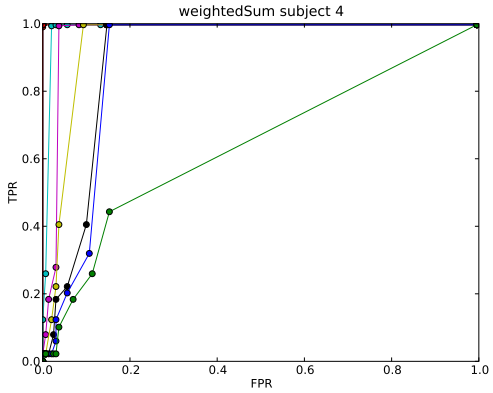

Fig. 7. Example of the extensive search procedure in the parameterization of the weighted sum operator for fusing subject 4 EEG and ECG modalities. Not all parameter results are shown for the sake of clarity. The ROCs (color coded) and its corresponding AUCs are computed on the fusion result. The parameters deliver several ROCs from optimal (red) to worst (green).

Once the optimal parameter set in terms of AUC is obtained, we attain the comparison of the performance for each subject. First it is worth illustrating what the goal of the fusion application is. For this purpose the fusion result is

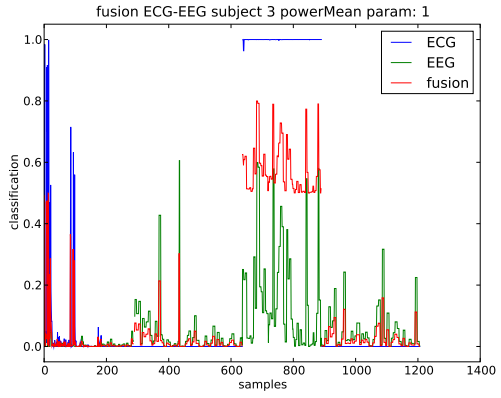

Fig. 8. Example of the compensatory behavior of the power mean operator on subject 3 classification scores (x-axis) when being optimally parameterized. True Positives, i.e. authentications of subject 3, are placed in the samples around the interval $[650, 900]$. The remaining ones correspond to results of impostor tests. In this case the power mean operator decreases the value on all the samples, but in such a way that TP maintain the maximal value.

shown in the sample domain for a particular subject's data (see Fig. 8). As it can be observed, the operator attains the maximization of the detection probability in the True Positive samples and its minimization in the False Positive ones. This is attained compensating the values on these two types of samples.

The performance evaluation however is done through an analysis of the ROCs and its corresponding AUCs. An exemplary subset of these results can be observed in Figs. 9, and 10. As it can be observed in this figure the performance of the fusion operator improves the performance of any individual modality. However we can distinguish among different types of improvement. In the cases where one of the modalities presents an optimal performance, i.e. its AUC is close to 1, the application of the fusion operator tends to reproduce the behavior of this modality (see Figs. 9a, and b). If the performance of one of the modalities is much worse than the other, even approaching the performance of random guessing, either we obtain a light improvement (see Fig. 9c) or reproduce the performance trend mentioned in the former case (see Fig. 9d).

The improvement is more clear in those cases where the performances of both modalities are commensurable (see Fig. 10). If the maximal FPR is similar, but the TPR differs, we can improve the performance in two different manners. An improvement in terms of TPR (see Fig. 10a) can be obtained in case the TPR is not large enough. Otherwise, i.e. TPR is large enough, the improvement is achieved in terms of FPR (see Fig. 10b, c, and d).

One further result of this test is the selection of the fusion operators to be used. As it can be observed in the different figures (see Fig. 10), the difference in terms of performance of the different fusion operators is not significant. This means that the selection of one operator or another will not significantly alter the final performance of the system. It is worth mentioning that the selection of the optimal parameter set is an important intermediate step in order to obtain this result.

Once we have selected the optimal parameter set for each fusion operator, we evaluate their robustness with respect to a change in the subject. For this purpose we compute the average performance in terms of AUC over the different subjects. We compare the average AUC when the operators are parameterized optimally for each subject with the average AUC when the operators are parameterized with their most robust parameter set. The obtained comparison is given in Table I. The most robust parameter set is obtained by comparing the average AUC over the different subjects for different values. These values (which can be observed in the third column of Table I) with a maximal difference between the average AUC over subjects and their variance are selected as most robust for each operator.

TABLE I

ROBUSTNESS EVALUATION OF OPERATORS W.R.T. A CHANGE IN SUBJECT. PERFORMANCE MEASURES OF THE DIFFERENT EVALUATED FUSION OPERATORS (FOP) WHEN COMPARING THE PERFORMANCE WITH THEIR OPTIMAL PARAMETER SET (PS) AND WITH THEIR MOST ROBUST PARAMETER SET. THE COMPARISON IS DONE IN TERMS OF THE OBTAINED AUC. $A\bar{U}C$: AVERAGE AUC OVER SUBJECTS. σ_{AUC}: STANDARD DEVIATION OF AUC OVER SUBJECTS.

FOP	performance	PS	$A\bar{U}C$	σ_{AUC}
power mean	optimal	-	0.7914	0.2471
	most robust	2	0.7756	0.0574
weighted sum	optimal	-	0.7907	0.2469
	most robust	0.9, 0.1	0.7831	0.0587
Yager S-norm	optimal	-	0.7378	0.1859
	most robust	121	0.7334	0.0332
Uni-norm	optimal	-	0.7798	0.2599
	most robust	0.97, 10	0.7644	0.0644
OWA	optimal	-	0.7788	0.249
	most robust	0.9, 0.1	0.7766	0.0594

As it can be observed the performance of the optimal parameter set and that of the most robust one does not differ more than 2% for any of the analyzed operators. This demonstrates the robustness of soft data fusion operators with respect to a change in the subject. One further interesting point is that the performance variance is smaller when applying the most robust parameter set. This fact can be explained easily from a numerical point of view, since the most robust parameter set selection has taken into account the variance with respect to a change of subject. Furthermore this makes the system performance more stable over a change of the subject.

Lastly, it is worth commenting on the analysis of the most robust parameter. Although all fusion operators present a similar performance, as mentioned earlier, the weighted sum proves to be the one with the most robust behavior with

respect to a change in the subject. In this context we point out the fact that the obtained weights reflect the importance of both modalities in the performance of the final authentication. Furthermore the OWA is however the operator with minimal difference between its average performance for the optimal parameter sets, and that of the most robust parameter set.

V. Conclusions and Future Work

We have demonstrated the performance improvement that can be achieved through the application of soft data fusion operators in a system of multi-modal biometric authentication. The fusion behavior of the five analyzed operators only differs slightly, at least on the preliminary results evaluated in this paper. Moreover the improvement depends both qualitatively and quantitatively on the relationship between the performances of the individual modalities.

One further result of the undertaken performance evaluation refers to the robustness of the operators with respect to a change of the subject being analyzed. Hence all the analyzed operators allow a robust parameterization. Therefore they can be used with a unique parameter set for all the analyzed subject set without downplaying its performance significantly. In this context it is worth pointing out the robustness of the weighted sum and the ordered weighted averaging (OWA) operators. Their difference in performance with respect to that of other operators is however small enough, to consider an equivalent behavior among the outperforming ones.

Future research work will take into account the extension of the presented results with respect to an increment in the number of modalities included in the system. Moreover we will evaluate the stability of these results when the subject being authenticated goes through different activities.

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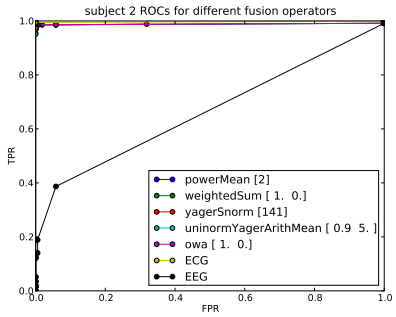
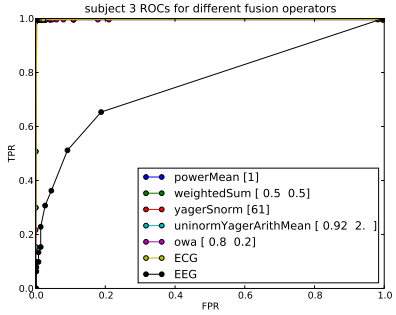
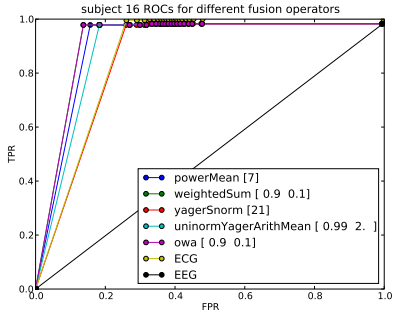


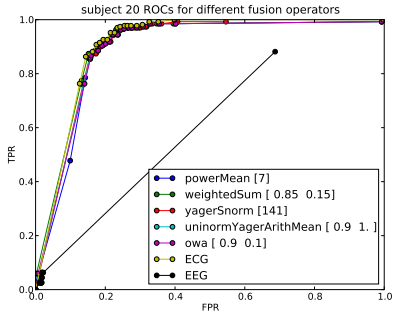
(a) Subject 2. ECG almost perfect performance.



(b) Subject 3. ECG almost perfect performance.

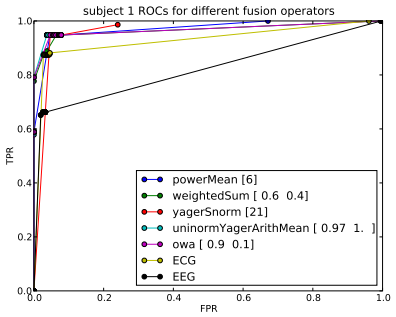


(c) Subject 16. Light performance improvement w.r.t. FPR.

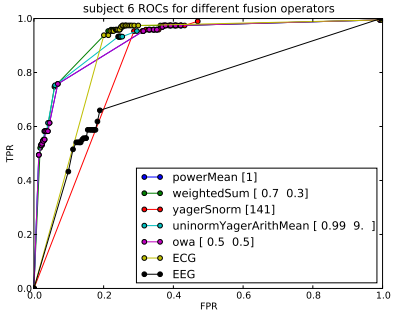


(d) Subject 20. ECG much better performance than EEG.

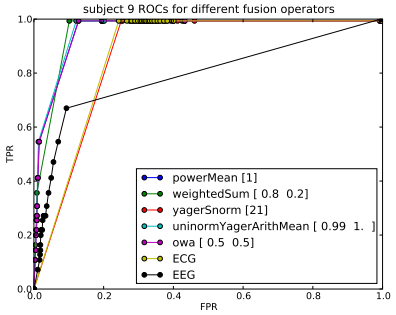
Fig. 9. Performance evaluation on fusion results for different operators. They present a minimal improvement due to a very good or very bad performance of one of the individual modalities, i.e. EEG and ECG (see legend). Comparison for different operators (see legend) on different subject data (see sub-figure captions). Parameters of the fusion operators are given in the legend.



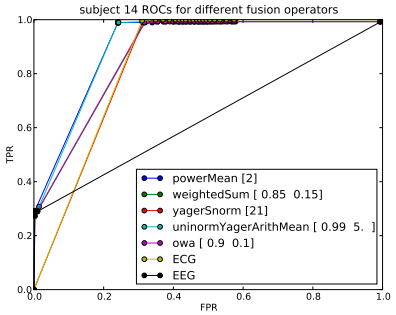
(a) Subject 1. Improvement w.r.t. TPR.



(b) Subject 6. Improvement w.r.t. FPR.



(c) Subject 9. Improvement w.r.t. FPR.



(d) Subject 14. Improvement w.r.t. FPR.

Fig. 10. Performance evaluation on fusion results for different operators. They present a significant improvement due to a commensurable performance of the individual modalities, i.e. EEG and ECG (see legend). Comparison for different operators (see legend) on different subject data (see sub-figure captions). Parameters of the fusion operators are given in the legend.

Appendix G

Stress Monitoring System based on EEG

This enclosed work that follows was published as a Conference Paper in the proceedings of the "FET European BEAMING project workshop and RAVE conference" organised in Barcelona on June 2011. For complete reference please see Riera et al. [56].

BEAMING/RAVE-11 Abstract

Barcelona, June 14th 2011

Stress Monitoring System based on EEG

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Abstract

1. In this work we present a BCI system able to provide information about the arousal and valence dimensions of emotions which in our case we want to relate with the stress level. This system can work in real time and could be used in many different applications such as neurofeedback applications, augmented reality in telepresence and in clinical Decision Support Systems (DSS) for treatment of pathologies such as psychological stress.

2. In the context of a European FP7 ICT project called INTERSTRESS (http://interstress.eu), Starlab has gathered 32 channel electroencephalogram (EEG) data to 12 participants to study the potential of extracting information about the stress level of the participants. In order to do so a protocol was defined, in which the participants had to perform different tasks:

- **Baseline:** participants were asked to stare at a cross in the computer monitor for 3 minutes
- **Relax:** participants had to close their eyes and relax for 4 minutes
- **Stroop Test:** participants had to perform a Stroop color-word (Jensen at al 1966) test for about 4 minutes.
- **Mathematical calculations**: the participants were asked to count down from a large prime number (2083, for example) in increments of 13 as quickly and accurately as possible. On every failure the participant had to restart at the beginning number. This task lasted for 4 minutes.
- **Reading:** participants were asked to read a short text and to pay attention since they are told that they will have to answer some question about the text at the end of the recording. This task lasted for about 4 minutes, depending on the reading speed of the participant.

A second part was also recorded, having the participants performing the same tasks (except the mathematical tasks in which we change the initial number and the increment was 17 rather than 13, and the text of the reading task, that was also modified) but now we introduce 3 actors to the participant telling them they are experts on non verbal communication and that they will be observing and taking notes. This is done with the purpose of to increasing the level of stress of the participants (Kirschbaum et al. 1993) At the end of the experiment we faked a blood sample extraction by introducing a ATS carrying a set of labeled tubes containing fake blood. After putting the plastic strip around the participant arm and opening the syringe, the participant was told that no blood sample was really needed. This was done to increase the arousal of the participants. Our aim in this study is to see if we can correlate the information extracted from the EEG with the different tasks performed by the participants, taking into account that each task has a different stress level, i.e. it is expected that the participant have more stress while performing the Stroop test and the mental calculations when he is observed by the actors, than in the relax task when he is not

observed. EEG has already been used for stress detection (Lewis et al. 2007), but in that case they were using a natural stressor (exam period versus exam free period to a group of students). In our case we developed a protocol in which we induce stress by making the participant perform different tasks. One of the aim of our study was also to find the best EEG locations by using a 32 EEG channel system. In a next stage the idea is to use the wearable and wireless ENOBIO sensor (Cester et al. 2008) for both the neurofeedback and VR platform developed in INTERSTRESS. This system is much more user friendly, it is easy to set up and only has 4 channels.

We also recorded Electrocardiogram (ECG) in order to extract the heart beat rate, electromyogram (EMG) from the zigomatic and corrugator muscle and Galvanic Skin Response (GSR) in order to see how these physiological parameters vary also as a function of the different tasks. We also recorded horizontal and vertical electrooculography (EOG) so we can use these signals to clean the artefacts they create in the EEG signal by applying a proprietary algorithm developed at Starlab with real time capability.

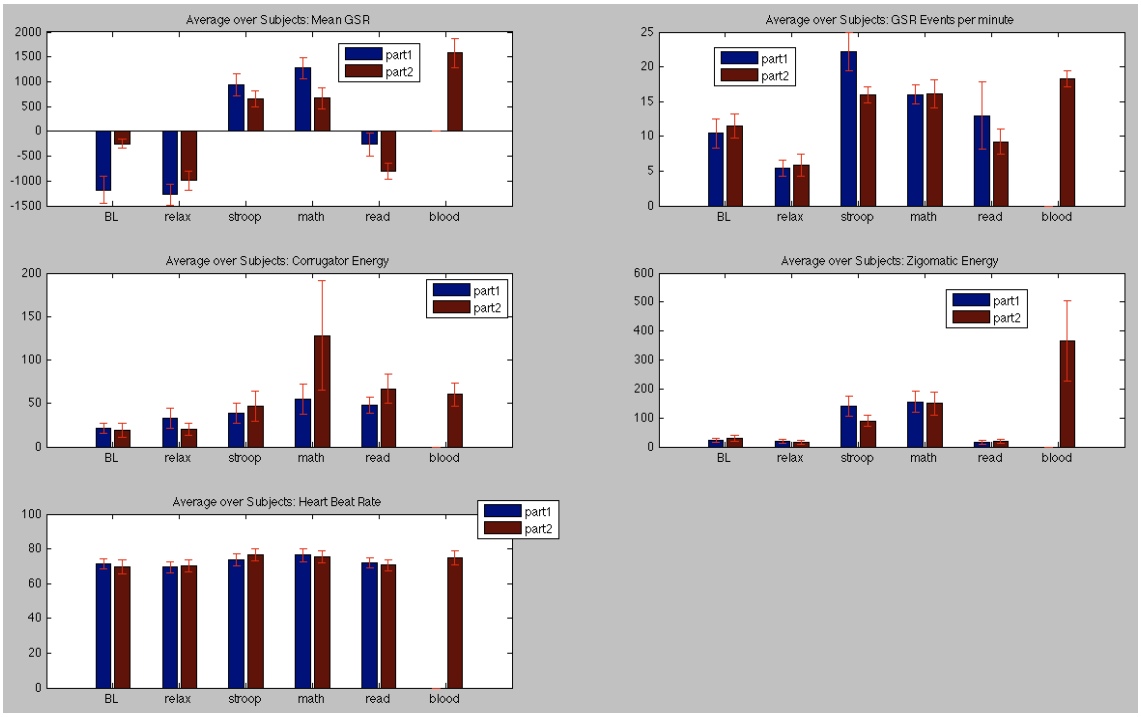

Figure 1: mean GSR, Number of GSR event, Zygomatic and corrugator EMG energy and HBR

We see in the precedent figure that the mean of the GSR (and the number of events, which are the number of maximums during the task performed) decreases in relax and then increases in the Stroop and the Mathematical tasks. It decreases again in the reading tasks to increase considerably in the fake blood sample task. A similar effect can be found in the zigomatic and corrugator EMG energy figures. The HBR increases in the Stroop task and in the Mathematical task, decreases in the reading task to increase again in the blood sample test. Finally we can also see that the mean of the GSR and the number of events of GSR are higher in the second part of the recording, when the actors are introduced, than in the first part, where no actors are present. These observations are consistent with our hypothesis: Stroop test, Mathematical task and the fake blood sample should be the more stressful situations. We can also see that the presence of actors in the second part of the recording does not seem to affect these physiological parameters.

Figure 2: Arousal-valence model of emotions. Y-axis represents the arousal while the x-axis represents the valence.

In this work, we are using the two dimensional scale of emotion representation proposed by Russell (Russell 1980). Emotions are mapped according to their valence (positive/approach versus negative/withdrawal), and arousal (calm versus excited). We can see in the next figure how basic emotions are classified using this model. The stress emotion would be somewhere between afraid and angry in the upper left quadrant.

3. Here we show that our system can be used to extract information about the emotional state of the subject, in terms of valence and arousal. This information can be extracted using only EEG as shown by (Zhang et al. 2009). We see that these 2 dimensions of emotion evolve in a specific way depending in the task the participants are performing. In the next figures we see the alpha-beta ratio of channel F3 electrode and the evolution of the alpha asymmetry between F3 and F4 electrodes. Alpha-beta ratio is related with the arousal dimension (Zhang et al. 2009) while the alpha asymmetry is related with the valence dimension (Lewis et al. 2007)

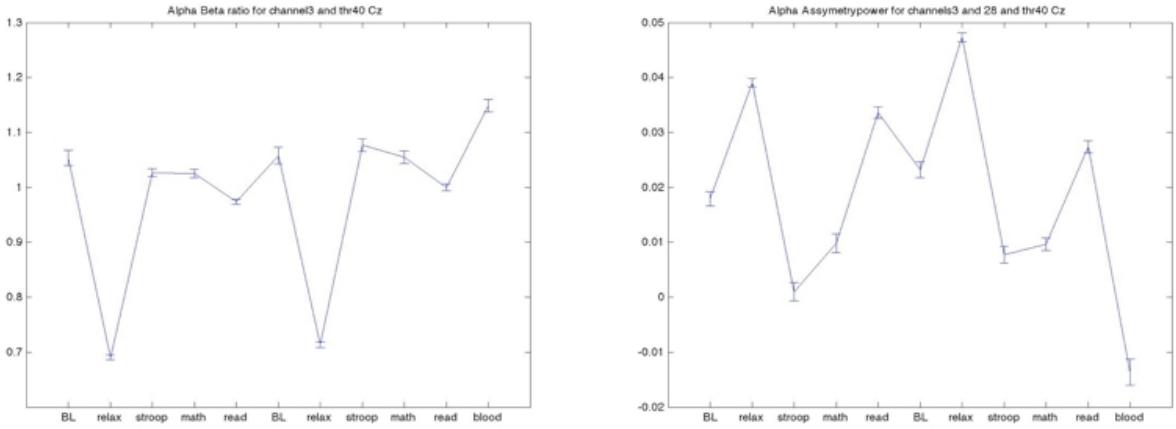

Figure 3: (left) Average over subjects of the Alpha-Beta ratio over the different tasks.(right) Average over subjects of the Alpha asymmetry over the different tasks.

In Figure 3 (left) we can see the average over 12 subjects of the alpha beta ratio. We see that this value decreases dramatically during the relax task. Then it increases during the Stroop test and the Mathematical calculations. Those task are cognitively demanding, and thus should be more stressful than relax and baseline. When the actors are introduced (from the second baseline (BL) to the end of the recording) we see that the alpha beta ratio increases compared to the part with no actors. Finally the fake blood sample shows the maximum values of this feature. In Figure 3 (right) a similar conclusion can be extracted. The Stroop test is the task that has the lower Alpha asymmetry in the first part of the recording (with no actors) and the fake blood sample the lowest Alpha asymmetry in the second part (with actors). In this case we cannot conclude that the presence of observers change the alpha

asymmetry.

4. The alpha-beta ratio results are consistent with the literature. Moreover we can see an effect on this value due to the presence of actors, that is the alpha-beta ratio is higher in the second part of the experiment when compare to the same tasks of the first part. On the other hand, the alpha asymmetry evolution in our work evolves in the opposite way as the results presented in the literature. The alpha asymmetry between left and right hemisphere is higher when the participant is performing the more positive tasks (BL, relax and read), and lower in the other tasks (Stroop test, mathematical calculation and fake blood sample).This is an interesting result and should need further research. The presence of the actors does not affect the alpha asymmetry feature in this case.

5. This study shows the possibility of implementing an emotion/stress/mental workload monitoring system through EEG data analysis. The EEG data processing steps include a high pass filter, an EOG correction algorithm and an artefact removal step. Then a spectral band analysis is performed in the alpha and beta range. At this stage of the research, a statistical analysis has been performed and a clear trend among the EEG features of the 12 subjects have been found: both alpha-beta ratio and alpha asymmetry evolve accordingly to the level of stress of each task. For a neurofeedback application this would be enough to modify for instance the size and color of a fire in a VR environment accordingly to the EEG stress related features. A user could then learn to relax using such application. A next step in our research is to apply computational techniques such as classification and fusion algorithms to compute the stress level of subjects in a more reliable way. More over, the results of our research shows that using only 2 EEG electrodes (F3 and F4) we would have enough information for our system to work. Another interesting and important characteristic of this work is that all the data processing steps can be performed near real time, thus allowing this system to work in several applications such as neurofeedback and augmented reality in virtual telepresence. More over this work was performed within a European project called INTERSTRESS which aim is to develop an advanced ICT based solution for the assessment and treatment of psychological stress. This ICT based solution includes a VR environment where the patients can learn to cope with stress, perform neurofeedback training and meet other virtual patients, among other functionalities. A biomonitoring system will record physiological data (including EEG, EMG, ECG, GSR, behavioral parameters, respiration, blood sample and saliva samples to measure the level of cortisol, among other parameters) and along with subjective questionnaires, a clinical DSS will help the doctor to diagnose and assess the stress level and the evolution of the patients using such a system.

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Appendix H

Resumen en Castellano

H.1 Introducción

Este documento es un resumen en Castellano de la Tesis Doctoral 'Computational Intelligence Techniques Applied to Electro-physiological Data Analisys' redactada por Alejandro Riera. La intención de este resumen es dar una idea clara y precisa de los estudios presentados en la tesis original. Para ello, y para que el documento no resulte excesivamente extenso, se han omitido tablas, figuras, lista de acrónimos, referencias, anexos y documentos insertados en la medida de lo posible. Todas estas partes se pueden encontrar en el documento original, si algún lector está interesado.

En esta tesis se ha trabajado sobretodo con señales de electroencefalografía (EEG) y en menor parte con señales electrocardiográficas (ECG), electrooculográficas (EOG) y electromiográficas (EMG). Estas señales has sido procesadas con técnicas avanzadas de tratamiento de señales y una vez las características deseadas han sido extraídas de ellas, se han aplicado técnicas de Inteligencia Computacional (IC) para analizarlas.

Las técnicas de tratamiento de señales incluyen el pre-procesado de las señales electrofiosiológicas, las cuales suelen estar contaminadas por artefactos de diversos tipos, como artefactos debidos al movimiento (por lo cual el contacto físico del electrodo con la piel padece pequeños movimientos que se traducen en cambios de potencial relativamente amplios), artefactos oculares (en particular el movimiento de los ojos y el parpadeo afectan enormemente el EEG). Para ello las señales han sido filtradas para eliminar bajas frecuencias de poco interés para nuestros estudios y que ademas suelen incluir parte de estos artefactos. En la mayor parte de los casos las señales también han sido filtradas pasa baja para eliminar altas frecuencias de poco interés para nuestros estudios. La etapa de pre-procesado también incluye referenciar los canales a un canal con poca actividad eléctrica (que puede ser el lóbulo de la oreja, la punta de la nariz o el mastoide). Finalmente, si después del pre-procesado aún nos encontramos con señales ruidosas, las partes de la señales ruidosas suelen ser descartadas. En cada caso se explicara que tipo de preprocesado se ha realizado con cada una de las señales.

El siguiente paso lógico es extraer información de estas señales. Las señales electrofisiológicas son series finitas que representan los cambios de voltaje de cierto electrodo (referenciado a otro) a través del tiempo. Estas señales suelen ser relativamente aleatorias a simple

vista (al menos el caso de EEG, ya que en el caso de ECG, la señal es muy característica, aunque también pueda contener ruido). A simple vista estas señales no suelen aportar mucha información, pero al extraer características de ellas, podemos entender de una manera mas eficaz la evolución y naturaleza de dichas señales. En esta etapa de extracción de características hemos trabajado con técnicas espectral (la transformada de Fourier), análisis de autoregresión y también hemos estudiado la relación entre la señal de pares de electrodos aplicando cálculos de coherencia, correlación, información mutua y también hemos aplicado una técnica llamada probabilidad de sincronización.

El siguiente paso en nuestro análisis ha sido estudiar las diferentes caraterísticas extraídas de las señales aplicando técnicas de IC. Estas técnicas incluyen clasificadores y algoritmos evolutivos, como los algoritmos genéticos. Como explicaremos mas adelante, dichos algoritmos nos han permitido seleccionar las características óptimas para luego poder aplicar sobre ellas clasificadores con el objetivo de encontrar tendencias interesantes en los datos.

Para finalizar la introducción, cabe señalar que en esta tesis se describen 3 investigaciones independientes pero que metodológicamente son relativamente similares.

- Biometría basada en señales electrofiosiológicas
- Características del EEG en sujetos de primer brote Psicótico
- Marcadores de Estrés en las señales de EEG

En la siguiente sección vamos a describir detalladamente cada una de las investigaciones realizadas.

H.2 Objetivos

H.2.1 Biometría basada en señales electrofiosiológicas

En la primera investigación hemos analizado datos de EEG, ECG y EMG desde un punto de visto biométrico: podemos identificar/autenticar a diferentes sujetos mediante estas señales? Son suficientemente únicas las señales de cada individuo como para poder distinguir entre ellas?

En esta investigación, hemos sobre todo utilizado señales de EEG y ECG, aunque también realizamos un experimento con señales EMG. El motivo por el cual hemos utilizado ambos EEG y ECG es porque el sensor utilizado para las tomas de datos tenía 4 electrodos, con lo que teníamos suficientes electrodos para grabar EEG y ECG simultaneamente. La configuración de los electrodos en todo los experimentos ha sido la siguiente: 2 electrodos en la frente para EEG (en Fp1 y Fp2), 1 en la cara interna de la muñeca izquierda para ECG y finalmente otro en el lóbulo de la oreja derecha como referencia. La tierra estaba puesta en el lóbulo de la oreja derecha.

Diversas características han sido puestas a prueba en la fase de investigación de este proyecto, y para el desarrollo de la aplicación final 5 características han sido tenidas en cuenta: la transformada de Fourier, análisis de autoregresión, coherencia, correlación e información mutua. Las dos primeras son calculadas para cada uno de los dos canales mientras que las tres últimas se calculan para el par de canales en cuestión, por lo que en total trabajamos con 7 características diferentes.

Brevemente, el funcionamiento del sistema es el siguiente. Primero un sujeto debe grabar su EEG durante 8 minutos (4 tomas de 2 minutos). Gracias a estas tomas, el sujeto puede darse de alta en el sistema. Utilizando estos datos, las 5 mejores combinaciones de características (i.e. las características más discriminativas para este sujeto en concreto) son calculadas. Hay que tener en cuenta que sumando las características y las 4 Funciones de Disciminación (FD) de nuestro clasificador (utilizamos Fisher Linear Discriminant Analisis (FLDA) en el cual implementamos 4 FD: Lineal, Diagonal Lineal, Cuadrático y Diagonal Cuadrático), tenemos (4x7) 28 combinaciones posibles. Esta información es entonces guardada en el sistema, y cada vez que el sujeto utilice el sistema, estos datos serán cargados para comparar la toma de autenticación actual con las tomas originales. Esta metodología, a la que llamamos 'Clasificador Personalizado', nos ha proporcionado buenos resultados, como veremos a en la sección H.3.1.

Para el caso del ECG, el sistema es muy similar al anterior, lo único que en este caso solo utilizamos 1 característica de la señal, que no es mas que la forma del complejo ECG procesado mediante técnicas de filtraje y normalización. Por lo tanto en este caso solo cargamos a la hora de la autenticación el clasificador óptimo para el sujeto en cuestión (tenemos 4 clasificadores, uno por cada FD).

H.2.2 Características del EEG en sujetos de primer brote Psicótico

En este proyecto se han analizado un set de datos EEG de 16 controles y de 15 sujetos de primer brote esquizofrénico (SZ), antes de tomar cualquier tipo de medicación. De este set de datos hemos realizado diferentes estudios ya que los sujetos de primer brote pueden subdividirse en varios grupos: 9 sujetos que han padecido un brote y luego han sido diagnosticados como SZ, 6 sujetos que también han padecido un brote pero que en este caso no han sido diagnosticados como SZ y finalmente 7 sujetos SZ unos meses después del primer brote tras seguir un tratamiento farmacológico. El objectivo de esta investigación es desarrollar un sistema capaz de clasificar controles versus SZ utilizando únicamente la señal EEG. Este sistema sería una herramienta muy útil para el diagnóstico de SZ. Al ser el EEG un registro completamente objetivo y barato, y en el caso de que la fiabilidad de dicho sistema sea alta, podría ser muy útil para los psiquiatras, como un fuente de información adicional además de las fuentes tradicionales, a la hora de diagnosticar pacientes.

El preprocesado de los datos ha incluido la aplicación de filtros pasa banda, la corrección de los artefactos oculares (el EOG tanto vertical como horizontal han sido también registrados) y los registros de EEG han sido cortados en épocas de 8 segundos. De la señal original de EEG, hemos aplicado 6 filtros pasa banda, y hemos trabajado en paralelo con cada una de esas bandas. Las Bandas Frecuenciales (BF) utilizadas son: de 4 a 8 Hz (Theta), de 8 a 10 Hz (Alpha1), de 10 a 13 Hz (Alpha2), de 13 a 30 Hz (Beta), de 30 a 45 Hz (Gamma1) y finalmente de 45 a 90 Hz (Gamma2).

Para este estudio hemos utilizado una una técnica llamada Probabilidad de Sincronización (PS) que nos da una medida de sincronía entre dos señales (en nuestro caso entre dos electrodos). La PS puede tomar valores entre 0 y 1. El registro incluía 64 canales, así que hemos calculado esta medida para cada posible par de electrodos. Al realizar esto obtenemos una matriz de incidencia (i.e probabilidad que el canal x y el canal y estén sincronizados). A partir de esta matriz, y aplicando un valor umbral, obtenemos un grafo. En otras palabras, si el canal x y el canal y tienen una PS superior al valor umbral, el nodo x y el nodo y están conectados. Para cada matriz de incidencia obtenemos varios grafos, pues hacemos que el valor umbral varíe entre 0.01 y 0.4. Como ejemplo ilustrativo podemos imaginar que si el valor umbral es suficientemente pequeño (0 por ejemplo), obtendríamos un grafo completamente conectado (todos sus nodos estarían conectados). Si por el contrario ponemos un valor umbral alta (1 por ejemplo) tendríamos un grafo completamente desconectado.

Los grafos son una entidad matemática muy utilizados en el análisis de 'Redes Complejas'. Esta rama de las matemáticas se aplica para el estudio de las relaciones entre diferentes entidades que se representan mediante nodos, y sus relaciones se representan mediante conexiones. En nuestro caso los nodos son los electrodos (64) y las conexiones representan si ambos electrodos actúan de forma similar o no.

Una vez que obtenemos los diferentes grafos, calculamos para cada uno de ellos dos características muy utilizadas en el análisis de Redes Complejas: el coeficiente de grupo (CC por sus siglas en inglés Clustering Coefficient) y la distancia media entre nodos (PL de Path Length). Finalmente obtenemos una gráfica de la evolución de CC en función del valor umbral y otra para el PL en función del valor umbral. Estos dos vectores son los que vamos a utilizar en la etapa de clasificación. Para cada sujeto tenemos un elevado número de vectores ya que extraemos un vector para cada época de 8 segundos y tenemos unas 150 épocas por cada sujeto. Además cada vector está compuesto por 40 elementos (hemos aplicado 40 valores umbrales) y tenemos 2 vectores, uno con los valores de CC y otro con los de PL. Finalmente teniendo en cuanta las 6 bandas frecuenciales, estamos trabajando con alrededor de 150*40*2*6=72000 para cada sujeto.

En este punto es donde hemos aplicado un Algoritmo Genético (AG) para seleccionar las mejores características antes de introducirlas en el clasificador. La función que hemos maximizado es el rendimiento del clasificador (número de sujetos correctamente clasificados sobre el número de sujetos totales). El resultado del AG son los puntos de los vectores, tanto como PL y CC, de la banda frecuencial con mayor poder discriminativo (los puntos que maximizan el rendimiento del sistema). También el AG nos proporciona la mejor Función de Disciminación (FD) del clasificador que utilizamos (en nuestro caso utilizamos Fisher Linear Discriminant Analisis (FLDA), en el cual utilizamos las mismas 4 FD que en la sección). Una vez hemos hallado estos punto podemos calcular el rendimiento de nuestro sistema para cada uno de los problemas de clasificación que hemos implementado.

Estos problemas son los siguientes: Control vs Brote (en el grupo brote juntamos a los sujetos de primer brote ya sean diagnosticados como SZ o no), Control vs SZ (en el grupo SZ juntamos a los sujetos diagnosticados como SZ ya sea antes (SZ pre) o después (SZ post) de tomar medicación), SZ pre vs nSZ pre (interesante caso en el que analizamos si somos capaces de predecir si un sujeto padeciendo un brote será diagnosticado como SZ o no), Control vs SZ pre, Con vs SZ post y finalmente SZ pre vs SZ post. Los resultados están descritos en la sección H.3.2

H.2.3 Marcadores de Estrés en las señales de EEG

En este proyecto se han estudiado las señales EEG para hallar indicadores de estrés. Para ello se ha diseñado un protocolo experimental cuyo fin era provocar a las sujetos diferentes niveles de estrés. Dicho protocolo contenía diferentes tareas descritas en la siguiente lista:

- Linea base: el sujeto debe mirar una cruz en la pantalla de un monitor.
- Relax: El sujeto debe cerrar los ojos y relajarse.
- Test Stroop: El sujeto debe leer en voz alta los colores de distintas palabras que denotan nombres de colores. El color de la palabra no coincide con su sentido.
- Cálculo matemático: El sujeto debe ir restando 7 repetidamente empezando por 2013, en voz alta. Cada vez que comete un error el sujeto debe volver a empezar desde 2013.
- Lectura: El sujeto debe leer una breve historia policiaca prestando atención, ya ha sido avisado que al final se le realizará un test de comprensión. Dicho test no se realiza en realidad.

Unos minutos después de este registro, se llevó a cabo otro registro que incluía las misma tareas con pequeñas modificaciones (el test Stroop contenía los mismos colores pero en distinto orden, el cálculo empezaba en 2017 y se tenía que restar 13 y finalmente el texto de la lectura era diferente). En este segundo test, se introdujeron 3 actores al sujeto como expertos en comunicación no verbal, y se explicó que irían tomando notas durante el registro pero que no iban a interferir en él. El propósito de la presencia de estos actores era la de incrementar el estrés social de los sujetos. De hecho, este procedimiento está basado en un método relativamente estándar en estudios psicológicos llamada test de estrés social de Trier. La última tarea a la que eran sometidos los sujetos era una 'falsa' toma de sangre: un actor disfrazado de enfermero entraba con una jeringuilla y unos tubos de ensayo llenos de sangre falsa y se le comunicaba al sujeto que una toma de sangre era requerida para finalizar el experimento. Evidentemente esta no se llevo a cabo, y el único objetivo era crear estrés en el sujeto.

En los experimentos se han registrados 32 canales de EEG en su configuración estándar 10-20, 2 canales para EOG vertical y horizontal, 4 canales de EMG facial (2 montajes bipolares para registrar la actividad del músculo zigomático y la del corrugador), 1 canal para ECG situado en la muñeca derecha y finalmente un montaje bipolar para medir la Respuesta Galvánica de la Piel (RGP), situado en la palma de la mano derecha.

Para cada una de estas señales hemos extraído diferentes características descritas a continuación:

- EEG: Se ha calculado la asimetría de la onda alfa para pares de canales simétricos, y también el cociente entre la onda alfa y la onda beta para canales individuales. Estas características han sido escogidas por aparecer en trabajos sobre estrés y emociones descritos en la literatura científica.

- EOG: Se ha utilizado para corregir la señal de EEG de los artefactos de los movimientos oculares y de los parpadeos.
- EMG: Se ha calculado la energía de la actividad del músculo zigomático y la del corrugador.
- ECG: Se ha extraído la frecuencia cardíaca.
- RGP: Se ha extraído por un lado el número de eventos (número de máximos relativos de la señal por unidad de tiempo) y la media de la señal una vez centrada en cero.

También se ha pedido a los sujetos que rellenasen un breve cuestionario después de cada tarea puntuando del 0 al 7 el nivel que sentían de distintas emociones (estrés, relax, ansia, felicidad, rabia, tristeza y disgusto).

En un primer estudio, se han analizado estadísticamente las tendencias de las distintas características de las señales, centrándonos en el EEG. Para ello se han realizado medias entre todos los sujetos y se han visto tendencias muy interesante y en acuerdo con la literatura. En un segundo estudio, se han utilizado técnicas de inteligencia computacional para clasificar los distintos niveles de estrés sujeto a sujeto. El rendimiento de los clasificadores ha resultado ser muy bueno como podemos ver en la respectiva sección de resultados H.3.3

H.3 Resultados y Discusión

H.3.1 Biometría basada en señales electrofiosiológicas

Los resultados de la tabla resumen nuestro trabajo en biometría aplicando un protocolo en el cual los sujetos debían permanecer sentados y relajados, con los ojos cerrados. Los resultados presentados son los obtenidos después de fusionar los resultados del módulo de biometría de EEG con el de ECG. En el caso de la función de decisión 1 utilizamos una linea en la cual parametrizamos solo 2 parámetros mientras que en la función de decisión 2 utilizamos una linea con 12 parámetros. En este segundo caso, la generalización de nuestro sistema a otros sets de datos podría estar comprometida, puesto que hemos ajustado la función de decisión 2 para maximizar el rendimiento de nuestro set de datos particular. Los resultados están dados en función del True Acceptance Rate (TAR) y False Acceptance Rate (FAR), medidas estándar en los estudios de biometría.

	TAR	FAR
Función de decisión 1	97.9%	0.82
Función de decisión 2	100	0

Table H.1: Resultados después de fusionar las modalidades de EEG y de ECG

Los resultados presentados en las siguientes tablas , y han sido obtenidos utilizando el mismo sistema biométrico, pero en este caso el protocolo de adquisición de datos no era tan controlado: los sujetos estaban sentados pero eran libres de realizar acciones típicas' que se

realizan en la oficina como teclear, hablar por teléfono, beber agua, usar el mouse, etc... Este hecho complica el análisis de las señales tanto de EEG como de ECG a causa de los artefactos tanto de movimiento como de EOG (parpadeos y movimientos oculares que afectan al EEG). Los resultados de la tabla muestran un rendimiento relativamente bajo pero claramente por encima de una clasificación aleatoria (i.e. 50%).

Toma	TAR	FAR (EER)
1	64%	36%
2	63%	37%
3	65%	35%

Table H.2: Resultados de Classificación para EEG (tomas 'Oficina') sin aplicar el módulo de corrección de artefactos

Para evitar en la medida de lo posible el efecto negativo de los artefactos, implementamos un algoritmo automático de corrección de artefactos. La tabla muestra como los resultados aumentan considerablemente al aplicar dicho algoritmo.

Toma	TAR	FAR (EER)
1	71%	29%
2	82%	18%
3	70%	30%

Table H.3: Resultados de Classificación para EEG (tomas 'Oficina') después de aplicar el módulo de corrección de artefactos

Finalmente la tabla muestra los resultados obtenidos únicamente con ECG.

Toma	TAR	FAR (EER)
1	87%	13%
2	88%	12%
3	88%	12%

Table H.4: Resultados de Classificación para ECG (tomas 'Oficina')

H.3.2 Características del EEG en sujetos de primer brote Psicótico

La siguiente tabla H.5 muestra los resultados obtenidos en nuestro análisis de datos de esquizofrenia, para cada uno de los métodos utiizados.

Los resultados están dados en función del porcentaje de sujetos correctamente clasificados. Como vemos, hemos aplicado diferentes métodos a diferentes problemas de clasificación. En el método 1, aplicamos un AG para maximizar el rendimiento de cada uno de los problemas de clasificación. Con este método obtenemos mejores resultados, pero hay que tener en cuenta que estamos maximizando el rendimiento utilizando todos nuestros datos, o en otras palabras estamos tuneando nuestro sistema para obtener el mejor rendimiento. Esto significa que si generalizamos el sistema a nuevos datos, el rendimiento no tendría porque mantenerse.

	method 1				method 2		method 3 with SL				method 4 with CO			
Classif. Problem	Perf.	Car.	FD	BF	Car.	Car.	Perf.	Car.	FD	BF	Perf.	Car.	FD	BF
CON vs Outbreak	80	CC	D. Quad.	Gamma1	70	CC	76.7	CC	D. Lin	Gamma1	73.3	CC	D. Lin	Gamma1
CON vs SZ	75	PL	D. Lin.	Theta	50	CC	65.6	PL	Lin.	Beta	68.8	CC	Lin.	Gamma1
SZ pre vs nSZ pre	83.3	CC	Lin.	Gamma1	58.3	CC	75	CC	Lin.	Gamma1	100	CC	Lin.	Gamma2
CON vs SZ pre	83.3	CC	Quad.	Gamma2	72.2	CC	72.2	CC	Lin.	Gamma2	83.3	CC	D. Lin.	Gamma1
CON vs SZ post	85.7	CC	Lin	Gamma1	78.6	CC	78.6	CC	Lin.	Gamma2	71.4	PL	Quad.	Gamma2
SZ pre vs SZ post	78.6	CC	D. Lin.	Gamma1	64.3	CC	64.3	CC	D.Lin.	Gamma1	64.3	CC	Quad.	Beta

Table H.5: Resumen de los resultados obtenidos por cada uno de los métodos utilizados y para cada uno de los problemas de clasificación planteados. Para el método 2, DF y FB son calculados para cada sujeto, por lo que no se muestran en la tabla.

Por esta razón hemos aplicado el método 2, en el cual dejamos siempre 1 sujeto fuera del AG, y una vez halladas las mejores características de este subset de datos, realizamos la clasificación del sujeto dejado de lado. Este procedimiento, que se llama 'leave-one-subject-out' y es una técnica estándar en técnicas de inteligencia computacional, se aplica para cada uno de los sujetos. Podemos ver que el rendimiento en general disminuye, pero por otro lado, la generalización de nuestro sistema no se ve comprometida. En este caso, como podemos ver en la tabla H.5 que los campos FD y BF no están indicados puesto que son calculados para cada uno de los sujetos.

En el método 3 hemos aplicado la clasificación utilizando todo el vector de características, sin aplicar el paso de seleción de características realizado por el AG. En este caso vemos que obtenemos unos resultados algo mejores que en el método 2 en algunos casos. En este caso la generalización de nuestro sistema no está comprometido tampoco, aunque como realizamos todos los posibles problemas de clasificación (por característica, FD y BF), estamos dando en la tabla H.5 los mejores resultados. En la figura H.1nos centramos en una solo característica, FD y BF, por lo que la comparación entre los distintos métodos se puede comparar más fácilmente.

Finalmente, el método 4 es igual que el método 3 pero en este caso utilizamos la coherencia entre los distintos canales en lugar de la PS. Los resultados son similares a los obtenidos en el caso de PS, aunque vemos una perfecta clasificación en el caso del problema SZ pre vs nSZ pre.

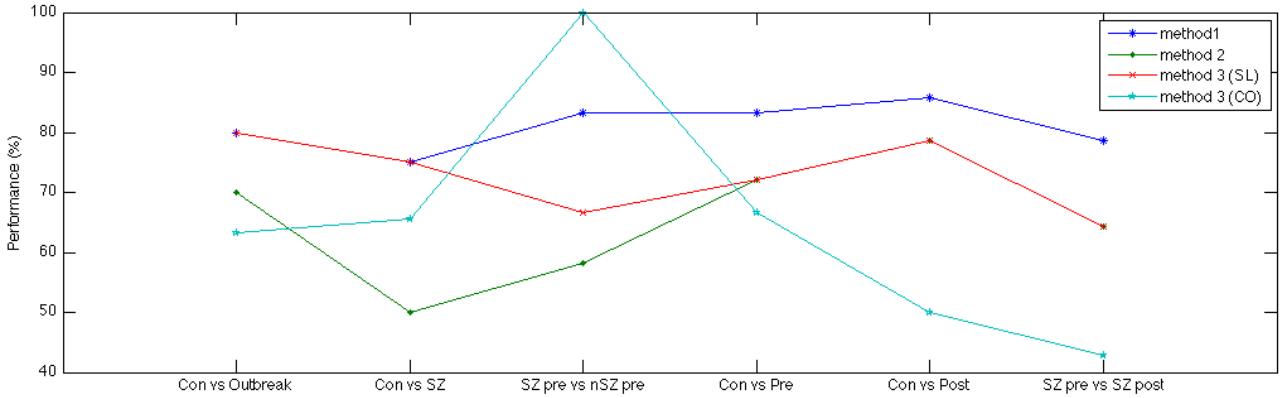

Figure H.1: Rendimiento para cada uno de los problemas de clasificación y por cada uno de los métodos aplicados.

H.3.3 Marcadores de Estrés en las señales de EEG

La siguiente tabla H.6 muestra los resultados obtenidos en nuestro análisis de datos de estrés. Como se ha comentado en la respectiva sección , primero se hizo un estudio estadístico en el cual se han hallado diferencias significativas tanto en la asimetría de la onda alfa como en el cociente entre alfa y beta.

Utilizando estas mismas características para canales simétricos, y aplicando técnicas de inteligencia computacional, hemos sido capaces de clasificar en que clase se encuentra el sujeto. Las tareas que hemos hemos utilizado son Linea Base 1 y 2 (nivel de estrés bajo), Stroop 2 (nivel de estrés moderado) y Toma Falsa de Sangre (nivel de estrés alto). Esta asignación subjetiva de nivel de estrés de estas tareas se ve apoyada por las diferencias estadísticamente significativas ($p \leq 0.05$) de las medidas electrofisiológicas periféricas, particularmente el número de eventos en la señal GSR. Los números 1 y 2 hacen referencia a si la tarea en cuestión se grabó durante la primera parte del experimento (sin actores) o durante la segunda (con actores).

Las clasificaciones se han realizado usando también la técnica 'leave-one-subject-out': todos los sujetos menos uno se utilizan para entrenar el clasificador y en un segundo paso testeamos con el sujeto que no hemos utilizado. Este procedimiento se hace para cada sujeto para maximizar el set de entrenamiento y a la vez el set de test.

Tarea	FP1-FP2	AF3-AF4	F7-F8	F3-F4	FC1-FC2	FC5-FC6	T7-T8	C3-C4	CP1-CP2	CP5-CP6	P7-P8	P3-P4	PO3-PO4	O1-O2
Linea Base1-Stroop2	54	54	58	58	54	54	63	58	50	63	**75**	63	58	46
Linea Base2-Stroop2	63	58	67	50	50	50	58	50	54	67	**83**	71	63	50
Linea Base1-Sangre	71	67	79	63	46	**88**	67	67	50	71	58	38	42	42
Linea Base2-Sangre	71	71	79	67	50	79	67	71	58	**83**	58	42	46	46
Stroop2-Sangre	63	67	58	58	54	63	63	58	38	75	**79**	63	58	38

Table H.6: Resultados de cada uno de los problemas de clasificación para cada par de canales simétricos. El mejor resultado de cada problema ha sido resaltado en negrita.

Podemos ver que para ciertos pares de canales, obtenemos unos rendimientos realmente elevados. En el caso del problema Linea Base1-Sangre obtenemos 88%. En el caso de los problemas Linea Base2-Stroop2 y Linea Base2-Sangre obtenemos un 83%.

Es interesante notar que estos resultados se han conseguido utilizando solo 2 canales de EEG (mas un referencia en Cz). De hecho nuestra idea era utilizar el mínimo número de canales posible para tener un sistema cómodo y fácil de usar.

H.4 Conclusiones

En este documento se han presentado de forma muy resumida las 3 investigaciones principales llevadas a lo largo de mi tesis doctoral: Biometría basada en EEG, diferencia en las características del EEG de una población de sujetos de primer brote psicótico y Marcadores de

Estrés basados en EEG. Las tres investigaciones nos han brindado resultados positivos y nos gustaría comentar en esta conclusión posibles aplicaciones de estos sistemas descritos.

En primer lugar no hay duda de que el ámbito de aplicación de un sistema biométrico suele estar ligado a la seguridad. Es cierto que el hecho de tener que poner un sistema de EEG resulta algo engorroso, aunque se está trabajando en hacer los sistemas mas pequeños y fáciles de poner y de usar, como es el caso de ENOBIO, un sistema desarrollado por Starlab Barcelona y que ha sido utilizado en esta tesis. En cualquier caso, en ciertas aplicaciones de alta seguridad puede resultar útil utilizar dichos sistemas como medidas de seguridad adicionales o incluso para fusionar varias modalidades biométricas para obtener un resultado realmente fiable. Además, nuestro sistema biométrico puede hacer biometría de manera continuada siempre y cuando el sujeto lleve el sensor puesto. Esto es una ventaja sobre los demás sistemas biométricos también puede extenderse este concepto a la monitorización del estado de los usuarios para no solo detectar si son quienes dicen ser, sino también para detectar si se quedan dormidos y pueden provocar un accidente (conductores de coches, controladores aéreos y en general cualquier persona que esté realizando tareas potencialmente peligrosas).

También podría resultar muy útil en entornos virtuales donde la gente intercambia información con avatares que dicen ser usuarios conocidos pero difícilmente se puede comprobar esa información. Utilizando nuestro sistema biométrico, los usuarios de entornos virtuales podrían estar seguros de la identidad de los avatares y estarían mas dispuestos a hacer transacciones con otros usuarios. Si además sumamos el sistema de estrés, podríamos hacer los entornos virtuales más reactivos a los sentimientos de la gente. Hay mucho estudios en estos campos y pensamos además que los entornos virtuales estarán cada vez más presentes en nuestras vidas.

Finalmente, es interesante el hecho de haber investigado sobre la búsqueda de características del EEG que no varían a lo largo del tiempo en un mismo sujeto, sino que son estables a lo largo del tiempo. De hecho esto es lo contrario que suele hacer los investigadores del campo BCI (siglas en ingles de Interfaz Cerebro Maquina). Ademas la metodología aplicada es novedosa al haber utilizado elementos del la Inteligencia Computacional como clasificadores y fusión.

En el segundo estudio hemos trabajado con un set de datos muy interesante en el cual teníamos registros de 64 canales de EEG de sujetos de primer brote psicótico tomados el día de su ingreso en urgencias y antes de iniciar un tratamiento farmacológico, y también de un set de controles. Hemos desarrollado un sistema capaz de clasificar entre sujetos con unos porcentajes de acierto realmente interesantes. Este sistema permitiría a los psiquiatras establecer diagnósticos mas acertados y sería beneficioso también a la hora de decidir que tipo de medicación tiene que tomar cada sujeto. Ha sido también interesante ver que las frecuencias que mejor resultados nos han dado eran las frecuencias altas gamma. Esto esta en acuerdo con la literatura. Ademas hemos aplicado un método basado en redes complejas y que también parece estar de acuerdo con la teoría de desconexión funcional como mecanismo para explicar ciertas enfermedades mentales. Seria muy interesante aplicar esta misma metodología a otras enfermedades y ver también si somos capaces de clasificarlas.

En la última investigación que hemos realizado, hemos diseñado un experimento para 'estresar' a los participantes y ver si podíamos detectar este estrés en el EEG. Los resultados han sido sorprendentemente buenos desde un punto de vista estadístico (haciendo medias sobre todos los sujetos). En este punto hemos aplicado técnicas de inteligencia computacional para

clasificar a los sujetos uno por uno y hemos sido capaces de predecir en que estado de estrés se encontraban con un grado de acierto de hasta 88%. Como hemos comentado brevemente arriba, pensamos que esta aplicación podría ser utilizada en entornos virtuales sensibles al nivel de estrés de los usuarios para que cambien en función de este. También podría ser útil para aplicaciones de neurofeedback en los cuales los sujetos aprenden a relajarse y/o a estresarse. Esto podría ser útil en terapias para sujetos que sufren de estrés crónico o estrés post-traumático.

Como último apunte queremos comentar que pensamos que la neurociencia va a ser la ciencia del siglo XXI como lo ha sido la física en el siglo XX. Grandes descubrimientos se han hecho ya en los últimos años, pero aun así quedan muchos misterios relacionados con el órgano mas complejo de nuestro organismo y seguramente el sistema mas complejo del universo conocido. Con esta tesis esperamos haber aportado nuestro granito de arena a esta fascinante rama de la ciencia.