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Biometrical and Psychophysiological Assessment through Biosensors

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RESUMO

O reconhecimento de padrões é crucial nas interações humanas. Permite, por exemplo, o reconhecimento da identidade e das reações de outros. Com um uso crescente de máquinas, sistemas de controlo e tecnologias de informação, tornou-se vantajoso que esses sistemas sejam capazes de fazer reconhecimento biométrico e psicofisiológico. Neste trabalho, é criada uma metodologia de suporte aos referidos reconhecimentos usando dados fisiológicos. Um método de extração de características e de classificação foi desenvolvido e diversos parâmetros de configuração do algoritmo foram minuciosamente estudados.

Para reconhecimento biométrico, é proposto um método parcialmente fiducial usando o sinal eletrocardiográfico (ECG). Para a segmentação do sinal de ECG em batimentos cardíacos, aplica-se um método fiducial que deteta os picos R, usando-os para referência de alinhamento dos batimentos. Para extração de características, aplica-se um método baseado em Análise de Componentes Principais (*Principal Components Analysis* - PCA). Finalmente, usa-se a distância Euclideana e um classificador *K-Vizinhos mais próximos* (k-NN) para a identificação de pessoas; para a autenticação apenas a distância Euclideana é usada. Com a metodologia proposta, são obtidos erros de 0% e 0.3% para a identificação e autenticação, respetivamente.

Para a avaliação psicofisiológica, são feitos dois estudos – classificação de emoções e de grupos populacionais (toxicodependentes vs. grupo de controlo) – usando aquisições de sinais associados à variação de volume de sangue ejetado, atividade electro dérmica e sinal respiratório. É então feita uma extração fiducial de características e aplicam-se dois métodos de classificação. O primeiro usa o PCA para conversão das características para um novo espaço que maximiza a diferença entre grupos de características, seguindo-se uma classificação baseada em distância Euclideana e k-NN. O segundo usa apenas distância Euclideana e k-NN. Embora a classificação de emoções não permita a discriminação entre diferentes respostas emocionais, foi possível distinguir entre toxicodependentes e grupo de controlo com um erro de 0%.

Palavras-Chave: Sinais fisiológicos, biometria, reconhecimento de emoções, análise psicofisiológica, Análise de Componentes Principais, K- *Vizinhos mais próximos*

ABSTRACT

Pattern recognition is crucial in human interactions. It allows, for example, recognition of others' identity and reactions to one's actions. With the increasing use of machines, control systems and information technologies in everyday life, it has become advantageous for those systems to be capable of doing human biometrical and psychophysiological recognition. This work develops a framework methodology for the mentioned recognition through physiological data. Both feature extraction and classification methods were proposed and developed, and different configurations of algorithmic and proposed system parameters were thoroughly studied.

For biometric recognition, a partially fiducial method using the electrocardiogram (ECG) is proposed. For the segmentation of the ECG signal into heartbeats, a fiducial method is applied in which the R peak is detected and used as alignment reference. For feature extraction, a non-fiducial method based on Principal Components Analysis (PCA) is applied. Finally, Euclidean distances and K-Nearest Neighbours (k-NN) classifier are used for user identification; the Euclidean distance is used for authentication purposes. Ultimately, 0% and 0.3% error rates are achieved for identification and authentication, respectively.

In psychophysiological evaluation, two studies are presented – emotion evaluation and population group classification (drug abusers vs. control group) – using Blood Volume Pulse (BVP), electro-dermal activity (EDA) and respiratory signal (RESP) acquisitions. Fiducial feature extraction is performed and two classification methods are applied. The first uses PCA for conversion of the initial features to a feature space that maximizes their differences, followed by Euclidean distance and K-NN classification. The second used only Euclidean distance and K-NN classification. Emotion assessment from the available data was not successful; in contrast, the distinction between population groups was achieved with a 0% error rate.

Keywords: Physiological signals, biometry, emotion recognition, psychophysiological analysis, Principal Components Analysis, K-nearest neighbours.

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ACRONYMS

AD	Absolute deviation
ANS	Autonomic Nervous System
BVP	Blood Volume Pulse
CG	Control Group
CNS	Central Nervous System
ECG	Electrocardiogram
EDA	Electro-dermal Activity
EER	Equal Error Rate
EG	Experimental Group
FIR	Finite Impulse Response
FTE	Failure To Enrol
HB	Heartbeat
HR	Heart rate
IAPS	International Affective Picture System
IBI	Inter Beat Interval
ID	Individual
IEigBs	Individualized Eigen Biosignal
K-NN	K-Nearest Neighbours
LDR	Light Dependent Resistor
NS	Number of samples
OEigBs	Overall Eigen Biosignal
PCA	Principal Components Analysis
PNS	Peripheral Nervous System
RESP	Respiratory Signal
RF	Respiratory Frequency
ROC	Receiver Operating Characteristic
SCL	Skin Conductive Level
SCR	Skin Conductive Response
SD	Standard Deviation
SNS	Sympathetic Nervous System

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

The Human species is not mistakable by any other known species. This happens because humans are very similar to each other when compared to other species. However, among approximately 7 billion human beings, there are no exact copies. Several factors, such as genetic / biological, social / behavioural and environmental, shape one's physical and psychological characteristics. Since early days, making the distinction between individuals and behaviours has been of extreme importance (Duda et al. 2001), e. g, distinguishing between males and females, distinguishing between familiar faces and strange ones, distinguishing between aggressive and calm people, distinguishing between other's positive or negative reaction to one's behaviour, etc.

Based on what has been mentioned so far, it is possible to verify that recognition of an individual's or a group's physical and psychological characteristics are needed. Recognition implies that a person/system is able to discover a common pattern in the element being recognized, memorize it and find the same pattern in a future confrontation with the element.

In today's society, with the rapid increase in communication, networking and mobility, automate-human interactions are becoming more and more important. This raises several questions, for example: "How is the system going to know that I am the owner of this bank account?"; "Am I sure that the system will not let others access my bank account?"; "If I am in a clearly emotional disruption state, shouldn't the system advise me not to withdraw so much money?". Machine recognition is thus

necessary for a human-automate interaction that is more accurate and more similar to human-human interaction, i. e., it is needed for automation, security and personalization of processes.

1.1.1 AUTOMATED HUMAN IDENTITY RECOGNITION

If previously introduced, humans are frequently able to recognize others, based on their visible physical characteristics, i. e., a combination of facial features, hair type, height, physical shape. Nevertheless, when one talks about automated human recognition, other common options come to mind, such as fingerprint recognition or iris scanning. These later options are not however used in human-human recognition. This kind of structures are too complex, and not typically accessed by the human senses, for the average human brain to be able to recognize, memorize a pattern in it, and use it as human-human recognition feature. Taking into account that the human body is an extremely complex organism and that it has a very large number of processes and features, one can infer that there might be several physical/physiological characteristics which may be used to distinguish and recognize individuals. These characteristics are generally called biometric features. *Biometrics* refers to the identification of humans by their characteristics or traits and will be further explored throughout this work (A. K. Jain et al. 2008).

1.1.2 AUTOMATED PSYCHOLOGICAL FEATURES RECOGNITION

Through the ages, first mainly for survival purposes and nowadays mainly for social purposes, it has been necessary for one to be able to recognize and understand self's and other's psychological characteristics. For example, a psychologist should be able to evaluate a persons' mental health, one should be able to recognize addictive behaviours in a friend or a relative, and children should be able to recognize their parents' reaction / emotions regarding their behaviour in order to classify it as good or bad.

Even without previous context knowledge, there are several physiological variants that one can identify in order to recognize psychological features, e. g., blushing, high heart rate and very open eyes can mean anger. However, most people can easily disguise their emotions or opinions. Automated psychological features recognition systems are harder to deceive since it is difficult to mask or alter physiological signals such as heart rate or sweat level. A known application of this topic is the *lie detector*. It consists of a polygraph that registers and measures physiological alterations caused by stressful situations such as lying (James Allan Matté 1996).

Automated psychological assessment can also be important for people that have difficulties in expressing their feelings, such as patients with autism spectrum disorders.

It is also known that conditions that cause modification in neuronal networks, such as neurodegenerative diseases, or the consumption of harmful substances, may lead to some physiological alterations. Some of these physiological changes can only be detected with

computational help. Trained recognition systems can detect abnormal physiological patterns and help the diagnosis of complex entities such as Alzheimer or drug addiction.

1.2 PROPOSED APPROACH AND THESIS GOAL

This thesis addresses the issues of automated human identity recognition and automated psychological features recognition using biosignals. The first is done using electrocardiographic signal (ECG) acquired in the fingers. The second uses Blood Volume Pulse (BVP), Respiratory (RESP) and Electrodermal activity (EDA) signals. We propose a methodological and algorithmic approach exploring pattern recognition techniques to simultaneously address emotion and identity assessment. The methodology starts by an adequate pre-processing of the signals. For human identity recognition, Principal Components Analysis (PCA) is used for feature extraction and dimensionality reduction and an Euclidean based k-Nearest Neighbours algorithm is used for classification. In psychological features recognition, two approached are used: differentiation of emotional responses and distinction between a drug abuser group and a control group. After pre-processing, fiducial features extraction is performed in the physiological signals mentioned. For classification two tests are made: using PCA for mapping of the features to a new space and dimensionality reduction followed by k-NN; and using the features extracted directly in the k-NN classifier, without the use of PCA.

The goals defined for this thesis investigation are thus:

1. Development of a methodology for pattern recognition and classification of physiological signals;
2. Application of the methodology for user identification and authentication;
3. Application of the methodology for psychophysiological evaluation;

1.3 NOVEL CONTRIBUTIONS

As result of this work, the following novel contributions were made:

- Proposal and development of a new user centred Principal Components Analysis (PCA) based framework for signal representation allowing an easy update of the database in each enrolment;
- Implementation and comparison of the proposed method with a population centred PCA framework.
- Use of the proposed methods for ECG representation, Eigen Heartbeats.
- Use of the proposed methods for feature representation and classification in BVP, EDA and respiratory signals.

- Characterization and study of the parameters of the implemented PCA + k-NN classifier;
- Characterization of electrophysiological responses, in a specific setting, in a population of drug abusers compared to a control group.

The work developed has been partially published in (Santos et al. 2012). Another paper has been accepted to *6th International Conference on Bio-inspired Systems and Signal Processing* (Santos et al. 2013).

1.4 THESIS STRUCTURE

This thesis is organised in 5 chapters.

The first is an introductory chapter, where the motivation of this work is explained as well as goals, novel contributions and structure of the thesis.

The second chapter presents the State of the Art. In it, the main concepts and previous knowledge required is exposed. Topics under the scope of pattern recognition, biometrics and psychophysiological evaluation are explored, as well as the physiological signals' knowledge.

The third chapter gives an overview of the framework methodology used to reach this work's goals. The feature extraction and classification methods used are described.

The forth chapter is where the results of applying the proposed methodology to real physiological signals are presented and discussed.

The fifth chapter concludes the dissertation, and presents ideas for future work.

CHAPTER 2

STATE OF THE ART

The work developed in this thesis involved knowledge in several different areas such as pattern recognition and classification, biometrics and psychophysiology. This chapter gives an overview of the state of the art in these topics'.

2.1 PATTERN RECOGNITION AND CLASSIFICATION

Over the past million years, pattern recognition has been essential for survival. One is constantly taking in raw information about one's surroundings and basing one's actions in the classification given to the different environment elements. In everyday life, one is constantly being challenged with pattern recognition problems like recognizing familiar faces, deciding whether the breakfast milk is spoiled or not by its smell, or identifying one's car keys by their feel in one's pocket.

Although it seems simple, pattern recognition is actually a very complex process and, the more complex the pattern, the more difficult it is to recognize it. Some patterns are not even recognizable by the human senses. Yet, machines have the potential to discover them. For that reason and for automation purposes, it is of great interest to design and build machines that can recognize patterns. Automated pattern recognition has currently many applications such as computer-aided diagnosis systems for support of doctor's interpretations and findings, automatic speech recognition (e. g., for replacement of human voice operators), classification of text into several categories (e.g. spam/non-spam email messages), the automatic recognition of handwritten postal codes on postal envelopes, biometrics, computer vision or, simply, in the suggestion of new purchases to users in online shopping websites.

According to (Duda et al. 2001), a pattern recognition and classification process comprises the following steps:

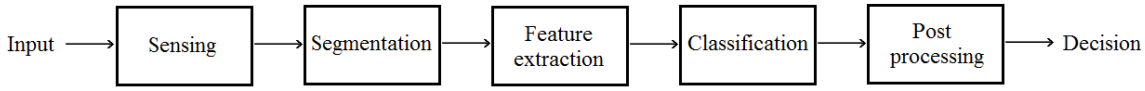


Figure 1. Pattern recognition and classification process

In this model, the sensing step is performed by a sensor that converts the raw input, such as images and sound, into signal data. The segmentation is applied to the signal data and it is the step used to separate the data of interest from the background. The feature extractor computes object properties that are useful for classification. Using these features, a classification process will assign each object to a category. A post processor can take into account other considerations, such as the effects of context and the costs of errors, in order to make an appropriate decision. This last step will not be considered in the model used; however, it can be of great interest in applications like automatic medical diagnosis where a wrong decision can have serious economical and heath consequences.

The design of a pattern recognition and classification system consists of some standard steps: data collection, feature choice, model choice, training and evaluation (testing) (Duda et al. 2001). Data should be collected both to train and to test the system, and its characteristics will affect both feature and model choice. The training process uses training (labelled) data to determine the system's parameters (decision rule). The evaluation is performed with new data (unseen by the system), and quantifies the quality of the classification system.

Reducing de number of variables is important for eliminating irrelevant data, enhancing learning efficiency, reducing the cost of (future) data collections and increasing predictive accuracy of the classifier. This can be done through feature selection (selecting a subset of the original variables for classifier design) or feature extraction (determining a linear or non linear transformation of the original variables to obtain a smaller set).

Feature selection has gained importance in areas where classification is done with small high dimensional samples, such as in Bio-informatics, for microarray data analysis. The goal of feature selection is to chose m most discriminatory features from the d features possible, with $m<d$. It should be noticed that the best sub-set of features will necessarily depend on the classifier chosen (Polikar 2006). Principal Components Analysis (PCA), also known as Karhunen–Loève transformation, is a data representation method widely used both for feature extraction and feature selection. It maps the input variables to another representation space, ordering the new vectors by the variance of the data represented. It is thus possible to eliminate the vectors that represent lower variance and the data, resulting in a dimensionality reduction with little information loss. One widely known application of PCA is in image processing and face recognition (Turk & Pentland 1991). Images are typically very high dimensional signals and face recognition algorithms can beneficiate from the use of PCA for data representation and compression. When one uses PCA for face representation, eigen-faces are created. Eigen-faces can be considered simply as a set of features which characterize the global variation among face images that efficiently represent the face information reducing computation and

space complicity. They extract the relevant facial information, which may or may not be directly related to human intuition of face features such as the eyes, nose, and lips (Lata 2009).

Concerning feature extraction, there are mainly two approaches described in the literature: fiducial, and non-fiducial methods. Fiducial methods consist of finding points of interest within pre-processed signals, and then representing the data by means of the features extracted from these points, such as corresponding amplitudes and latencies. Non-fiducial methods, on the other hand, consider the whole signal's shape and the patterns extracted from it are used as features. Most of the times, it implies converting the signal to a different data representation. Partially fiducial methods are also possible; these use fiducial methods and non-fiducial methods in different stages of the process. For simplicity, these are also denoted as non-fiducial methods.

The complexity required for the classifier is usually inversely proportional to the efficiency of the feature extractor. There are several classifiers with different complexities and the choice will depend on the problem. Detailed information about several classifiers can be found in literature (Duda et al. 2001). There are two kinds of classifiers (Webb & Copsey 2011): supervised (e.g., discriminant analysis) and unsupervised (e.g., clustering). In supervised classification, the user can either set the decision rule or provide some labelled data (class prototypes) for training the system. In unsupervised classification, no previous training is done and, usually, the user has to define the number of classes.

Several frameworks for pattern recognition have been traditionally formulated, such as template matching, statistical methods, syntactic or structural and neural networks. The statistical approach has been the most studied and used. Recently, neural network methods have been receiving increasing attention (A. Jain et al. 2000).

In a statistical approach, data is represented by a set of features. Those features strive to represent the different pattern vectors in order for them to belong to different categories in compact and disjoint regions. Examples of statistical classifiers are Support Vector Machines (a generalized linear classifier with a maximum-margin fitting criterion), k-NN (one of the simplest and, simultaneously, more robust classifier), Bayesian classifier (the learning agent builds a probabilistic model of the features and uses that model to predict the classification of a new example), Naïve Bayes (Bayesian method that assumes independent feature models).

Even though classifiers were traditionally used separately, some studies have been investigating if there is a performance increase when using a combination of the output of several classifiers. This type of classification is particularly useful for data with complex decision boundaries, where there might not exist a single classifier that can reach a satisfactory performance. More information about fusion of classifiers can be found in literature (Ruta & Gabrys 2000).

In this study, Principal Components Analysis (PCA) and k–Nearest Neighbour (k-NN) are used as feature extraction / data dimensionality reduction methods and classification methods, respectively. Due to time restrictions, no other feature extraction methods were implemented; however, within the context of the investigation group where this work was developed, other feature extraction methods and data analysis approaches were tested on the same application data herein explored (D. P. Coutinho et al. 2010; D. P. Coutinho et al. 2012a; André Lourenço et al. 2011). K-NN is a very robust

classification method being thus adequate to small datasets such as the ones used in this work. These two methods are further described in the following sections.

Finally, for system evaluation two perspectives are commonly used. The first consists on estimating the overall error rate, by computing the fraction between the number of errors committed by the classifier over the total number of tests done. The second, use in binary systems, is a Receiver Operating Characteristic (ROC). In a binary system two outcomes are possible: positive (when the classification hypothesis is validated) and negative (when the classification hypothesis is not validated). However, due to classification error among the positives there are true positives (correct positive classification) and false positives (incorrect positive classification or false acceptance). Similarly, among the negatives there are true negatives (correct negative classifications) and false negatives (incorrect negative classification or false rejections). The ROC curve is created by plotting the fraction of false positives out of all the positives (false acceptance rate) versus the fraction of false negatives out of the negatives (false rejection rate), at various decision settings (such as a threshold parameter). For quantification of the systems performance, the equal error rate (EER) can be calculated. EER is the location on the ROC curve where the false acceptance rate and the false rejection rate are equal. In this work this method is used for characterizing the performance of the developed human authentication systems.

2.1.1 PRINCIPAL COMPONENTS ANALYSIS (PCA)

PCA is a common technique for finding patterns in high dimensionality data, being also commonly used for dimensionality reduction and data compression.

PCA is a statistical method that aims to decompose a set of data into linearly uncorrelated variables (eigenvectors). Each observation in the data set can be reconstructed by a linear combination of the eigenvectors. Therefore, each observation can be represented by a set of coefficients and the corresponding eigenvectors.

Let $X = \{X_1, \ldots, X_n\}$ denote the set of signals, with each X_i corresponding to a time series or feature vector. The PCA method decomposes the data into linearly uncorrelated variables (eigenvectors). Each observation in the data set can be reconstructed by a linear combination of the eigenvectors. Thus, each observation can be represented by a set of coefficients and the corresponding eigenvectors (Smith 2002).

The PCA method can be summarized as follows:

a. Compute the mean of the data: $\frac{\sum X_i}{n}$

b. Subtract the mean from data: $X_0 = X - \frac{\sum X_i}{n}$

c. Calculate the covariance matrix: $C = E\{X_0 \cdot X_0^{'}\}$

d. Determine the eigenvalues (λ_i) and the corresponding eigenvectors (V_i) of the covariance matrix *C*. The number of eigenvectors found should be the minimum between the number of features (dimension of each data occurrence) and the number of occurrences (*n*) minus one: $\min(n, dimention\ of\ X_i) - 1$

e. Sort the eigenvectors and select the ones with highest eigenvalues (higher energy) for data compression.

f. Each signal, X_i, is decomposed as a linear combination of the set of eigenvectors, $X_i = \sum c_i V_i$, where coefficients c_i are given by the projection of signal X_i into the eigenvector (inner product): $c_i = X_i \cdot V_i$

The higher the eigenvalue, the higher the variability of the data captured by the correspondent eigenvector. If an eigenvector has a low correspondent eigenvalue, one can say that the eigenvector has low energy. Low energy eigenvectors can be eliminated without significant impact in the total data shape. The relation between energy cut and data compression level is not linear; a low cut in energy generally translates in a higher data compression. The relations between data compression, data energy, eigenvectors and eigenvalues are represented in equations (1) and (2).

$$Compression = \frac{Number\ of\ eigenvectors\ kept}{Total\ number\ of\ eigenvectors} \quad (1)$$

$$Energy = \frac{\sum of\ the\ eigenvalues\ \ kept}{\sum of all\ the\ eigenvalues} \quad (2)$$

2.1.2 K–NEAREST NEIGHBOURS (K-NN)

K-NN is one of the simplest classification methods and it is one of the first classifiers used when there is little or no prior knowledge about data distribution. It measures the distance between the new object's features and the templates known by the classifier. The new object is then classified as belonging to the category of the majority of its *K* closest neighbours.

To find the distances between samples and templates, it is several different metrics can be used. The most commonly used is the Euclidean distance. Let x_i be an input sample with *p* features $(x_{i1}, x_{i2}, x_{i3}, \dots, x_{ip})$ and *n* be the total number of input samples $(i = 1,2,3, \dots, n)$, then the Euclidean distance is given by:

$$d(x_i, x_l) = \sqrt{(x_{i1} - x_{l1})^2 + (x_{i2} - x_{l2})^2 + \cdots + (x_{ip} - x_{lp})^2} \quad (3)$$

More information about this method can be found in literature (Duda et al. 2001).

2.2 BIOMETRIC RECOGNITION

Biometric recognition is an application of pattern recognition. It relies on physical or behaviour traits analysis in order to identify subjects.

The need for secure and reliable identification systems has grown in the past years mainly due to rapid advances in networking, communication and mobility. Biometric systems have been included in several applications, such as commercial (access control, computer login, e-commerce, banking, etc.)

government (driver's license, national ID card, border control, etc.) and forensics (corpse identification, criminal investigation, parenthood determination, etc.) (A. K. Jain et al. 2008).

2.2.1 BIOMETRIC SYSTEMS

User recognition systems based on biometrics comprise two main phases (A. K. Jain et al. 2011): enrolment and identification/authentication.

One is only able to recognize a person if one has been previously introduced to that person. Similarly, for a system to be able to identify or authenticate a user, he or she must be known to the system beforehand. The enrolment phase is responsible for the registration of the user biometric modality into the biometric system. At the enrolment phase, the user provides both his / her identity (such as the user's name) and the associated biometric modality sample, acquired by an appropriate sensor and acquisition device. After adequate processing, one or more templates of the acquired modality are stored in a database for future reference, and the user is said to be enrolled into the system. The processing phase usually comprises a quality evaluation procedure; if the acquired signals fail to accomplish the quality check there is what is known as a *failure to enrol* (FTE) error.

After enrolment, one of two methods can be used: identification or authentication.

At the identification phase, the user is required only to present the biometric modality at the sensor level; the system then processes this data, comparing it with the templates previously stored in the database (template matching 1:all). If the acquired biometric data is similar enough to one of the enrolled user's template, the present user will be classified with the corresponding identity. Otherwise, the system will reject the user.

In authentication, the individual intends to be recognized according to a claimed identity. For that, the user has to give the system, not only the biometric modality, but also the information about whom he says he is (i.e. user name). The system will compare the authentication data, with the templates available for the claimed user identity (template matching 1:1) in the database. If the acquired biometric data is close enough to the one kept as a template, the present user will be validated as having the claimed identity. Otherwise, the user will be rejected.

Concerning the correctness of the system decision, either it provides the correct decision (by correctly identifying the user or by denying the access to an impostor), or it incurs in error, rejecting a legitimate user (known as a *false rejection error*), or makes a wrong identification (*false acceptance error*).

Figure 2 gives a schematic description of the enrolment, identification and authentication phases for a general biometric system.

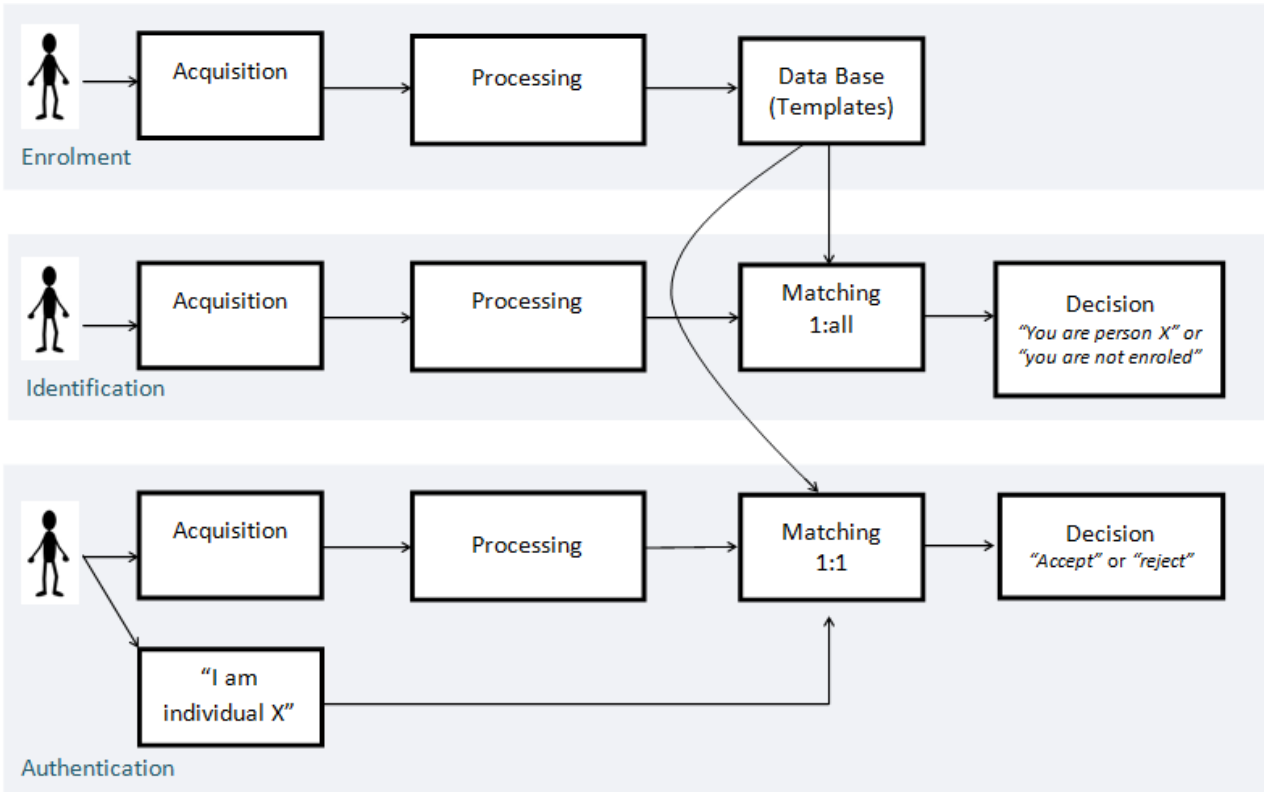


Figure 2. Schematic description of enrolment, identification and authentication process

2.2.2 TRAIT SELECTION

For identification suitability, the traits chosen should be universal (every user should possess it, leading to low *failure to enrol* rates), unique, permanent (or sufficiently invariant), measurable, acceptable, with high performance and have low circumvention (forging or mimicking) (A. K. Jain et al. 2011). Some of the most commonly used biometric characteristics are: fingerprint, palm print, iris, face, gait, ear, voice, keystroke, signature, DNA and retinal scan. Fingerprint and face recognition are two of the most commonly known methods. DNA and retinal scan are considered very secured and accurate.

The fingerprint has been used for many decades and it is one of the most used biometric features. It is easy and cheap to acquire and it is also distinctive. However, it is easily spoofed (e. g. by scars) or forged (e. g. using latex fingers or latent fingerprints).

Face recognition is how most humans recognize each other. It is completely non-invasive which makes it very acceptable. Nonetheless, acquisition can be tricky; there are several restrictions on how the facial images are obtained, e. g. background and illumination should be controlled. Also, face recognition can be ineffective if the subject presents simple changes like a moustache.

DNA is the deoxyribonucleic acid that contains the genetic information necessary for every organism development. It can identify, with a very small error, every individual. However, its processing is difficult (it requires an expert) and slow. It is mostly used in forensic applications.

Retinal scan is claimed to be the most secure biometric since it is not easy to change or replicate the retinal vasculature. However, for acquisition it requires a conscious effort on the part of the user, since he has to peer into an eye piece and focus on a specific point, affecting negatively the public acceptability of the method.

2.2.3 ELECTROCARDIOGRAM AND ITS USE AS A BIOMETRIC MEASURE

The trait used as biometrics in this study is the Electrocardiogram (ECG). The heart, the organ responsible to pump the blood through the body by successive contractions, is a type of involuntary muscle and it is capable of generating its own electrical stimuli needed for contraction. The electrocardiogram is a recording of the variation of the potential generated by the heart's electrical activity. The ECG signal has mainly been used for heart rate monitoring, determination of the electrical axis of the heart and clinical diagnosis of heart diseases, such as arrhythmias, myocardial ischemia and infarction or pericarditis.

2.2.3.1 The Heartbeat

The heart is composed by two separate pumps that work together, a right half and a left half. The right half receives the blood coming from the whole body and pumps it to the pulmonary arteries. The left half will receive the oxygenated blood from the lungs and send it to the rest of the body. Each half has a filling pump - the auricle - and an ejecting pump - the ventricle. The auricles fill the ventricles and these will produce the contraction power needed to pump the blood.

A heartbeat is a complete cardiac cycle. In each cardiac cycle the heart will contract and pump the blood through the body. The contraction is triggered by a bioelectrical activation signal, generated in special modified cardiac cells controlled by the autonomic nervous system. The signal is then transmitted through the heart as an action potential. An action potential is one of the ways for an animal organism cell to transmit information to other cells; it is basically the transmission of an electrical signal through a specific path. It comprises a quick depolarization phase - a change in a cell's membrane potential, making it more positive, or less negative - and a repolarisation phase - the return to a negative membrane potential.

As explained before, the ECG is a record of the electrical activity of the heart. It has a characteristic shape composed by 5 main waves. Each segment of a heartbeat electrical record is correspondent to a heart phenomenon Figure 3.

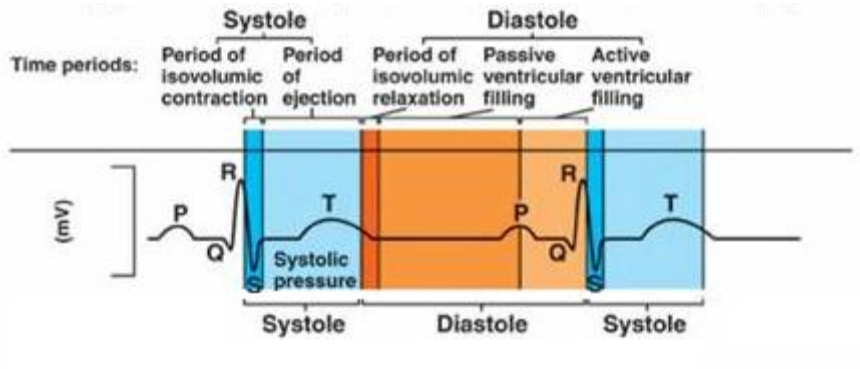


Figure 3. Typical heartbeats and correspondent cardiac events (Seeley et al. 2003)

A normal ECG has a P wave, a QRS complex and T wave. The P wave results from action potentials that cause the depolarization of the myocardium - the cardiac muscle - and marks the beginning of the auricular contraction. The QRS complex comprises three waves: Q, R and S. It is originated by the ventricular depolarization and marks the beginning of the ventricular contraction - systole. The T wave represents the ventricular repolarisation and precedes the ventricular relaxation - diastole.

2.2.3.2 Biometric perspective

Human hearts are similar from individual to individual and produce comparable electrical records. However, there are no exact copies. There exists anatomical / physiological diversity in different individual's hearts, and therefore an ECG signal differentiation between individuals is to be expected. Figure 4 illustrates the different ECG shape of three individuals. Through pattern recognition techniques, this variability can be detected, allowing the differentiation and the identification of individuals based on their ECG signals. It exists, however, some intra-subject variability that affects the recognition accuracy. This variability comes from emotional alterations and from eventual modification through time of the heartbeat. Heart rate modifications are not expected to have a big influence in the recognition rates since it affects mostly the inter beat interval (Fatemian & D Hatzinakos 2009) which not considered in the typical heartbeat windows.

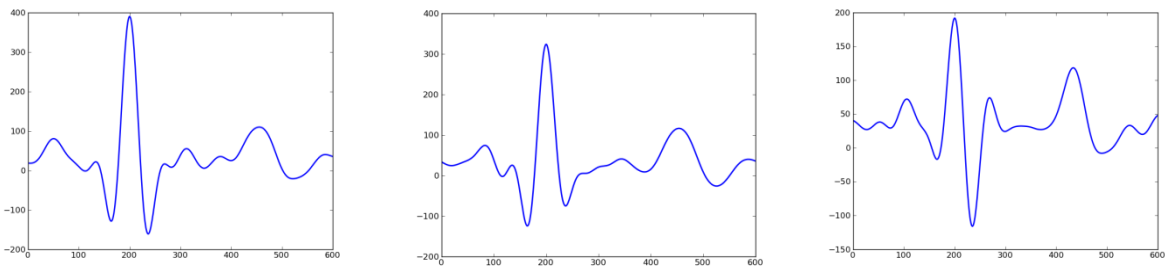


Figure 4. ECG shape of 3 different individuals

The EGC signal surpasses some of the limitations of common biometrics methods; it can only be taken from a living individual, through direct contact or close proximity to the body, making it difficult to deceive or imitate from latent or unauthorized reproduction of the patterns as in the fingerprint method

or the voice/face recognition method. It is practically spoof prove since one cannot modulate or disguise one's ECG signal. Also, it is correlated with the emotional state of the individual that is being identified, making it possible to detect if the person is being forced to do it. (Medina & A. L. . Fred 2010) Regarding ECG acquisition, there are several techniques and places where it can be collected, some more intrusive than others. Recent work has shown that high recognition rates are achievable, having also focused on overcoming the intrusiveness of traditional chest-mounted systems, by performing data acquisition at the hands and fingers using dry electrodes (André Lourenço et al. 2011). Still, several open problems persist. The fewer the leads, the easier it is to do the acquisition; however, the amount of noise collected increases, requiring a more complex signal processing.

The universality of this trait will depend on the type of feature chosen: fiducial and non-fiducial. ECG signals are very complex and variable and sometimes it is difficult to detect fiducial points, even for the human eye. Therefore, fiducial methods have a relatively high FTE rate. On the other hand, non-fiducial methods have low FTE rates.

2.2.3.3 Overview of Studies of ECG as Biometrics

Biel et al. (2001) was a pioneer in the use of ECG as a biometric modality. They have started by using a chest 12-lead ECG setup, which was unpractical to use in an everyday biometric system, but ended up concluding 1-lead was enough. All the acquisitions were done at rest. They have used a fiducial approach where 30 fiducial points were extracted from each ECG heartbeat signal, from a population of 20 individuals. Using PCA on the classes obtained, they have managed to obtain 100% recognition rate.

Shen et al.(2002) used a template matching technique that achieved 95% identity verification accuracy, a neural network classifier that led to 80% accuracy, and a method combining both techniques that achieved 100% accuracy, among a dataset of 20 individuals. Using the same combined technique (Shen 2005) reported 100% recognition rates for predetermined groups of 10, 20, and 50 subjects; for a pre-determined group of 100 subjects, 96% recognition rate was found; finally, a recognition rate of 95.3% was reported for the complete set of 168 subjects

Hugo Silva et al (2007) used acquisitions taken with a one lead chest setup in 26 subjects performing a cognition task. Fiducial feature extraction and feature selection was performed; a feature subspace ensemble method was then used resulting in a 99.97% recognition rate.

S. a. Israel et al. (2005) reported 100% accuracy in subject identification when using standard linear discriminate analysis (LDA) for individual waveforms classification and mapping to the identity of the subject. Acquisition were done while the individuals were performing high stress and low stress tasks and the authors ended up concluding that the method tried is invariant to stress stats.

Wang et al. (2008) used a feature extraction method based on a combination of autocorrelation analysis (AC) with the discrete cosine transform (DCT). This is a non-fiducial method since it does not require segmentation of the ECG signal into heartbeats, with only the R peak detection being needed for the QRS window identification. This method allowed 97.8% accuracy on a universe of 13 subjects.

With a QRS-complex detection algorithm and the discrete wavelet transform for feature extraction Chiu et al. (2008) manage to obtain a 100% accuracy for identification and verification rates of 0.83% of false acceptance rate (FAR) and 0.86% of false rejection rate (FRR) in a universe of 35 subjects.

In Chan et al. (2008), PQRST complexes are detected and averaged in order to compute and average ECG. For classification a distance measure based on wavelet coefficients is used. Finally, 89% identification accuracy was achieved on a dataset of 50 individuals

D. P. Coutinho et al. (2012) compared a fiducial (mean waves and 1-NN) with a non-fiducial (String Matching and 1-NN) approach. One-lead chest ECG acquisitions with no position or movement limitation were acquired from 51 subjects while performing a cognitive task. For the fiducial method 99.85% accuracy was obtained and for the non-fiducial 99.39%.

D. P. Coutinho et al.(2010) uses ECG recordings from 19 subjects acquired during a concentration task on a computer. They performed a non-fiducial feature extraction based on data compression techniques, namely the Ziv-Merhav cross parsing algorithm for symbol sequences.

Most of the existing ECG-based biometric identification systems rely on a fiducial approach (Biel et al. 2001; Shen et al. 2002.; Silva et al. 2007; Israel et al. 2005). However, non-fiducial methods are also referenced in literature (Chiu et al. 2008; Chan et al. 2008). Partially fiducial methods have also been successfully issued, proposing an initial segmentation of the ECG, centred on the detection of the R peak, followed by non fiducial processing and data representations, such as the use of compressing coding (D. Coutinho et al. 2011; D. P. Coutinho et al. 2010). For simplicity, these will also be denoted as non-fiducial methods.

Agrafioti (2011) is one of the first works taking into account intra subject variability. She uses a Linear Discriminant Analysis (AC/LDA) algorithm in a small scale and large scale recognition system. The results obtained in the large scale scenario were discouraging - 45.5% equal error rate (EER). This error is mainly related to the fact that, in large scale, there is no adequate training set, i. e., the population of enrolees is unknown at the time of LDA training. However, small-scale recognition has a better performance, obtaining a 12% EER.

A summary of these studies is presented in Table 1.

The work proposed in this thesis is closely related with the works by J. Irvine & A. (2009) and S. Israel & M. (2010), where PCA is applied. However, while in previous works an eigen-heartbeat is computed from the overall population, our work proposes individualized eigen-heartbeats computations, which characterize each individual.

Table 1. Summary of previous studies.

Reference	Acquisition	Feature	Method	Subjects	Accur.
(Biel et al. 2001)	Chest	Fiducial	PCA	20	100%
(Shen et al. 2002)	Chest	Fiducial	Template Matching + DBNN	20	100%
(Hugo Silva et al. 2007)	Chest	Fiducial	FSE	26	99.97%
(S. a. Israel et al. 2005)	Chest/neck	Fiducial	LDA	29	98%

(D. P. Coutinho et al. 2012b)	Chest	Fiducial	Mean Waves + 1NN	51	99.85%
(D. P. Coutinho et al. 2012b)	Chest	Non-fiducial	String Matching + 1NN	51	99.39%
(Chiu et al. 2008)	Chest	Non-fiducial	Wavelet Distance	35	100%
(D. P. Coutinho et al. 2010)	Chest	Non-fiducial	Cross Parsing + MDL	19	100%
(Wang et al. 2008)	Chest	Non-fiducial	AC/DCT+K-NN	13	97.8%
(Chan et al. 2008)	Finger	Non-fiducial	Wavelet Distance	50	89%
Proposed	Finger	Non-Fiducial	PCA + K-NN	65	100%

2.3 PSYCHOPHYSIOLOGY

Psychophysiology is a brunch of psychology that studies the physiological correlates to psychological events. It describes the mechanisms that link psychological processes, like emotions, motivation or attitude, to physiological responses of the organism. This relation's study involves pattern finding in physiological signals acquired in certain psychological and psychosomatic conditions (Ax 1964).

One of the main application fields is the study of psychopathological entities on psychosomatic conditions (min/body relationships in health and diseases). Some examples of classic psychosomatic diseases are asthma, hypertension, gastritis and headaches caused by stressful situations.

Psychiatric disorders like anxiety, depression, mania, drug abuse or schizophrenia, are very difficult to diagnose and treat due to their nature. Psychophysiological studies are one of the approaches used for non-subjective diagnosis and treatment of psychopathologies (Fowles 1988). An example of a physiological treatment approach for a psychological disease is the prescription of antidepressants to improve depression symptoms.

The Human Nervous System (HNS) is the system responsible for the connection of psychological and physiological events and it is a good start for psychophysiological events' study; it is thus described in the following subsection.

This thesis work will focus on emotional pattern finding in humans with a drug abuse clinical record and a control group. Also, drug abusers' psychophysiological profile will be compared with the control population's profile. Therefore, emotions theory and psychophysiological effects of drug abuse are addressed in the next subsections.

2.3.1 THE HUMAN NERVOUS SYSTEM – THE LINK BETWEEN MIND AND BODY

The connection between what one thinks / wants and what one does / the way one reacts is controlled by the human nervous system (HNS). It ensures body control and it is responsible for signal transmission through the body.

It is divided in two systems: central nervous system (CNS) and peripheral nervous system (PNS). *"Unlike the neighbouring discipline of brain imaging, psychophysiology has always included both central and peripheral systems in its purview and has been dedicated to understanding interaction between central and peripheral biological systems since its inception"* (Davidson 2003).

CNS is body's control centre. It is constituted by the brain and spinal cord and it is responsible for receiving and analyzing sensory information, storing some of that information deciding on which action to take and, triggering reactions accordingly.

PNS is exterior to the CNS and comprises sensory receptors (nerve ends that detect environmental stimuli), nerve cells (connect the CNS to the PNS), ganglia (mass of nerve cell bodies) and plexuses (extensive of nerve cell networks). It gathers information from different sources, both internal and external, and retransmits it to the CNS through nerve cells.

PNS is subdivided in two branches: somatic nervous system and autonomic nervous system (ANS).

SNS is responsible for transmitting action potentials from the CNS to skeletal muscles - muscles attached to the skeleton. Skeletal muscles are voluntarily controlled by the somatic nervous system, enabling one's conscious moments like raising an arm, jumping or producing the necessary movements for correct diction of words.

ANS transmits action potentials from the CNS to smooth muscle tissue, cardiac muscle and glands. These are all involuntarily and unconsciously controlled structures. For example, one is not able to control one's heart movements, digestive movements or adrenaline releases. The autonomic control mainly regulates the internal environment in order to maintain the body's homeostasis and provides support to complex behaviours, such as emotional reactions.

In turn, the ANS is also divided in sympathetic (SNS) and parasympathetic systems. The sympathetic branch promotes activity and prepares the body for action; the parasympathetic branch restores the bodily functions to a rest or vegetative state.

In short, the sensory part of PNS starts by detecting stimuli and sending them to the CNS. CNS is a very important and efficient processing centre that analyses the stimuli and triggers an effective answer to it. This answer will be sent by SNP action potentials to muscles and glands that will concretize the answer.

More information about the human nervous system can be found in (Seeley et al. 2003).

2.3.2 NON-INVASIVE PHYSIOLOGICAL DATA ACCESSING

It is normal to feel one's heart pounding when one is scared, to yawn when one is bored, to sweat when one is nervous or to blush when one is embaraced. In generic terms, it is possible to

perceive physiological alterations caused by psychological events, e. g., emotions. These alterations are mediated by the peripheral nervous system and can be measured and quantified using biosensors. Biosensors are devices that can detect electrical, chemical or physical measures of a biological system.

(Larsen et al. 2003) reviewed a series of studies that showed evidence of correlation between peripheral physiological measures and emotions. For example, happiness and disgust were characterized by decreased heart rate, anger was characterized by increased heart rate and increased skin temperature, and fear by increased heart rate and decreased skin temperature.

In this thesis work three biosignals are used for psychophysiological assessment: Blood Volume Pulse (BVP), Respiratory signal (RESP) and Electrodermal activity (EDA). Their acquisition will be explained in the methodology section.

2.3.2.1 Blood Volume Pulse

Clinically, BVP has a variety of applications such as heart rate measurement, detection of relative vasodilatation or vasoconstriction, and detection of changes in blood pressure. BVP measurement can also give information about changes in sympathetic arousal since vasomotor activity – activity that causes the vessels to contract or dilate – is controlled by the sympathetic nervous system.

Blood Volume Pulse is obtained by measuring the volume variations of an organ caused by variations in its blood volume – plethysmography. When the heart contracts, a blood flow is ejected through the arteries causing an enlargement of those vessels. This phenomenon is easily and non-invasively detected in limb extremities and earlobes. For example, if one's fingertip is pressed, one will have the sensation of "heart beating in the fingertip". What is being sensed are the volume changes. The BVP sensor does this measure by applying a light source to the skin and measuring the alterations in the reflected light – the amount of light that reaches the photosensor is directly related to the blood volume in the tissue. It is, thus, called Photoplethysmograph, i. e., an optically obtained plethysmograph.

2.3.2.2 Respiratory signal

Although it is not usually thoroughly studied in the affective computing framework, the respiratory signal has the potential of offering important emotional information. Intuitively, this can be noticed in situations of laughter, when one's respiratory signal increases frequency, or sudden fear, when the respiration almost stops.

Unconscious ventilation is maintained by the autonomic nervous system answering automatically to the body's need for more oxygen, for example, in a stressful situation where the body prepares itself for a rapid escape. However voluntary control is also possible. One can stop breathing to dive or control the air flux in order to speak correctly.

The respiratory sensor is constituted by a large Velcro belt and with a small elastic part. The Velcro belt is placed around the thorax and the elastic will stretch as the subject's chest expands. The amount of stretching in the elastic is measured as voltage change and recorded.

2.3.2.3 Electro-dermal activity

The skin has electrical properties that can change in a relatively small time frame. EDA is a term used to refer to changes in the skin's ability to conduct electricity. These changes have been repeatedly proved to correlate with emotional changes. (Sequeira et al. 2009)

The changes in conductivity are related to the amount of sweat in the skin. Salty water (the main constituent of sweat) is a good conductor so it will decrease the skin's resistance to electricity or conversely increase its conductance.

Sweat glands, in which sweat is produced, are mainly located in the hypodermis of palmar and plantar regions and, as every gland, are controlled by the ANS, more specifically, the sympathetic nervous system.

There are two main components in the EDA signal: electro-dermal level (skin conductive level, SCL) and electro-dermal responses (skin conductive response, SCR). Electro-dermal level corresponds to slow spontaneous electrical fluctuations of sweat gland activity, which result from the interaction between tonic discharges of sympathetic innervations and local factors (skin temperature and hydration). Electro-dermal responses are correlated with phasic sympathetic nervous discharges, and are characterized by their amplitude and temporal characteristics.

The EDA sensors are usually placed in the palmar region. There are two types of EDA recordings: the ones that do not use an external current, endosomatic, and the ones that use external current, exosomatic (Figner & Murphy n.d.). Exosomatic techniques are further distinguished by whether a direct current (DC) or an alternative current (AC) is used. In DC current case, keeping the voltage constant results in the measurement of skin conductance, as it reflects how well the skin conducts a current; while when current is kept constant, skin resistance is measured, as it reflects the electrical resistance of the skin. In the AC current case, keeping effective voltage constant results in the measure of skin admittance while keeping effective current constant results in skin impedance.

2.3.3 EMOTIONS THEORY

The definition of *emotion* is not consensual. (Mauss & Robinson 2009) reported that the most consensual model of emotional response *"starts with appraisal of the personal significance of an event, which in turn gives rise to an emotional response involving subjective experience, physiology and behaviour"*. In simple terms, emotion can be defined as a positive or negative affective reaction to an event.

Emotions are ordinarily thought of as discrete entities. One usually refers to one's emotions in words like happiness, sadness, madness, boredom, anxiety, etc. However, the idea that different discrete emotions have distinct physiological signatures is not well reasoned in literature. Instead, the majority of the studies point to a continuous emotions space supported by relations between different emotions' dimensions such as arousal (how "activating" an emotion is) and valence (how pleasant an emotion is). Discrete emotions can be, to some degree, related to a continuous emotion space. For

example, anger can be characterized by high arousal and negative valence, happiness by low arousal and positive valence, and sadness by low arousal and negative valence. Figure 5 illustrates the position of some known discrete emotions in the valence/arousal space.

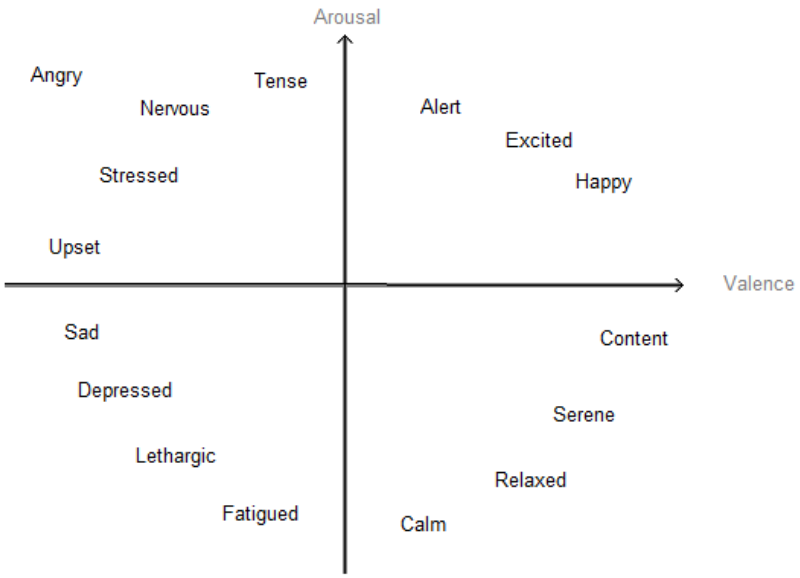


Figure 5. Discrete emotions in the valence/arousal space (the picture is merely indicative, discrete emotions' position should not be interpreted strictly)

In this thesis work emotion measurements were chosen to be taken from peripheral physiology (ANS response). According to (Mauss & Robinson 2009), valence and arousal are the emotional dimensions with better sensibility to the parameters measured in this study. A summary of emotional spaces can be found in (Mauss & Robinson 2009).

2.3.3.1 Emotions Recognition

Common sense says that the best time to ask for a raise is when one's boss looks happy, that one should keep away from a furious stranger in the street, or that one should try to comfort a sad friend. For a healthy social live it is crucial to be able to recognize another person's emotions. Machines are becoming more and more important in nowadays' society and they are playing critical roles in communication, being a part of common day-to-day tasks. Therefore, similarly to what happens in human-to-human interaction, it can be very interesting to have machines that can interpret human emotion. For example, having a personal computer that keeps the user from making big money transfers when the user is depressed; having a cell phone that checks if an angry user really want to send a text message; a wrist band that notifies a family member of successive emotional disturbance episodes of an elder alone at home; a computer mouse that is able to spot learning difficulties of a child playing didactic computer games. Recently, science has recognized the importance and potential applications of automatic machine recognition of emotional patterns. That field of studies is part of a larger branch called *Affective Computing*.

In *Affective Computing*, emotion recognition is done mostly through the analysis of the same events that make humans recognize emotion, i. e., as facial expressions, body movements, voice

behaviour and several physiological manifestations (e. g. heart rate, sweat level, etc). Several acquisition and processing techniques are used in order to obtain information about these events. A review of some of these techniques can be found in (Tao & T. Tan 2005). As example of some studies done in this area one has: Picard et al. (2001) applied Fisher projection to a large set of features extracted from four physiological signals, obtaining a 81% recognition rate on eight classes of emotion. Some examples of studies done in this area; Canento (2011) used a leave-one-out cross-validation k-N classifier and Principal Component Analysis and observed that different emotions could be differentiated with accuracy ranging from 30% to 97.5%; Medina & A. Fred (2010) used unsupervised learning techniques for assessing the continuous evolution and the separability of the stress states. Other examples of projects under this subject can be found in the MIT Affective computing website (M. M. Lab n.d.).

2.3.3.2 Emotions elicitation

Daily life is full of emotion triggering episodes; however, in laboratory a protocol is necessary for emotion elicitation. Several techniques for elicitation have been described in literature such as films, audio clips, pictures, memories or a combination of these methods (Margaret M Bradley & Peter J Lang 2007). Emotion elicitation is not trivial. Similar shapes can trigger very different emotions depending on the context (e. g. a hose and a snake) and the exact same object in the same context can trigger different emotions in different people. For example, the reaction to a dog's picture of a person who is afraid of dogs will not be the same as that of a dog lover person. Researchers have been trying to develop elicitation methods for correct and standard evaluation of emotions among different trials and laboratories. One example of this is the International Affective Picture System (IAPS, pronounced "eye-aps") in which this thesis work's dataset obtainment protocol is based. It comprises a large set of colour images that aim to trigger different emotions. The images are rated by men and women in terms of valence, arousal and dominance (Margaret M Bradley & Peter J Lang 2007). This system is used worldwide, providing a controlled emotional evocation and allowing a comparison between studies using this set.

2.3.3.3 Psychophysiological alterations in drug abuse patients

It is known that drug abuse can cause behaviour alterations and diverse physical damage, namely, neurological damage. Several studies have proven psychophysiological alterations in subjects with addictive behaviours, influenced by the type of drugs and patterns of consumption. For example, Richards et al. (2011) proved, through the use of catecholamine levels' measurement and cardiovascular responses, that the functioning of the autonomic nervous system is altered in chronic cigarette smoking; Verdejo-García et al. (2004) concluded through literature review that neuropsychological impairments have been consistently shown to be related to drug use and proved through metabolite analysis and functional neuroimaging techniques that same statement; Hoaken & Stewart (2003) relate drug abuse with a higher tendency to a violent behaviour; Sinha et al. (2009) uses behavioural distress responses, cardiovascular measures and salivary cortisol alterations in response of emotional cues to evaluate alcohol addiction.

Understanding which physiological alterations exist in drug abusing subjects can help in diagnosis and treatment of addiction and weakening or eliminating addictive habits and cravings.

In this work, a non-invasive assessment of the ANS will be tried to characterize abusing and control populations. Detail about the populations will be given further on.

CHAPTER 3

METHODOLOGY

The goal of this work is to perform a biometrical and psychophysiological evaluation of different people or groups of people based on pattern recognition in different physiological data. For that purpose, the methodology used follows the general steps of a pattern recognition and classification process, described in Chapter 2.

In this work, the s*ensing* step is referred to as *acquisition* and it is done by biosensors. However, there was no acquisition protocol implemented in this work. Instead, data sets previously acquired are used. The data sets are described in Chapter 4. The *segmentation* is from now on referred to as *pre-processing* and comprises several steps described further on. Pre-processing is different according to the classification purpose and type of the biosignals acquired. For biometric recognition using ECG signals, pre-processing comprises filtering, segmentation and outlier removal, while for psychophysiological evaluation only filtering is done. The feature extraction procedure is also different for the two tasks. In biometric recognition, a non-fiducial method is applied, using PCA to convert the heartbeats to a different representation space. For psychophysiological evaluation a fiducial method is applied. The classification process is common to all the evaluations done and uses the Euclidean distance and a k-NN algorithm.

Accordingly, the process followed is pictured in Figure 6.

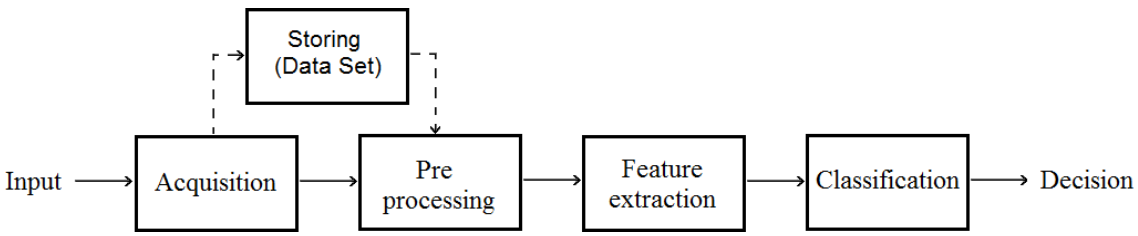


Figure 6 Schematic description of the pattern recognition method used in this work

Further explanation about the different steps implemented is given in the following sections. Due to the different steps required for pre-processing and feature extraction, the methodology will be divided in: *Biometrical data and Psychophysiological data.*

3.1 BIOMETRICAL DATA

The ECG signal can be measured at different places of the body, such as the chest, neck, wrists or fingers/hand palms. Having as goal increased usability and minimal intrusiveness, a one-lead finger ECG acquisition setup with dry electrodes was used (André Lourenço et al. 2011). The main problem with this configuration is the amount of noise inherent to it. This difficulty is hereafter compensated with adequate pre-processing. This step is applied to all the data acquired, i. e., both in the enrolment step and in the identification step (please refer to Figure 2, in Chapter 2).

3.1.1 PRE-PROCESSING

In order to deal with the noise inherent to the finger/palms acquisition, a sequence of pre-processing steps is proposed, and summarized in Figure 7, comprising filtering, segmentation into heartbeats, and, finally, outlier removal. These steps are described next.

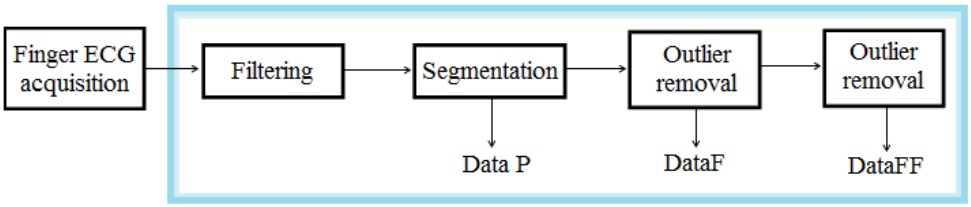


Figure 7. ECG pre-processing steps (framed). Individual heartbeats, obtained after segmentation, and first and second stages of outlier removal are designated, respectively, by DataP, DataF and DataFF.

3.1.1.1 Filtering

The ECG signals measured at the hands or the palms can be affected by multiple sources of noise (motion artefacts, power line noise, and electromyographic noise). A FIR band-pass filter was used (order 301, using a Hamming window), with 5-20Hz cut off frequencies, to limit the bandwidth of the raw input signals, and thus reduce, or even eliminate, some of these artefacts.

3.1.1.2 Segmentation

The segmentation step built on the work of Engelse and Zeelenberg (Engelse & Zeelenberg 1979) for offline QRS detection, adapting their algorithm for real-time QRS detection. A detailed description of the algorithm and comparison with offline approaches can be found in literature (A. Lourenço et al. 2012). The algorithm detects the R peaks and creates a window going from 0.2 seconds before the R-peak until 0.4 seconds after the peak. The fragment of signal that is inside that window is considered

to be a segment. Accordingly, one segment has 0.6 seconds. Since the sampling rate was of 1000 Hz, one considers each segment as a sequence of 600 points, where the R-peak is centred at point 200 (Figure 9).

3.1.1.3 Outlier removal

After segmentation, there was a clear need to remove outliers from the signal, either due to excessive noise not handled by the filtering step, or segmentation errors. An example of an outlier is shown in Figure 8. For that purpose, a simple outlier removal heuristic based on the median of the signal in selected points was created.

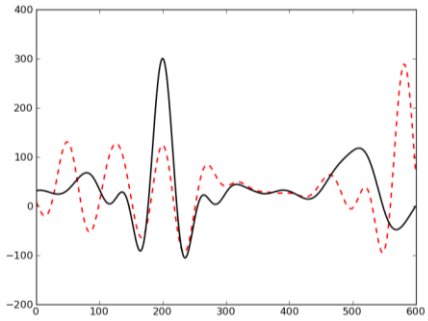


Figure 8. Outlier example (dashed curve) versus a typical heartbeat (solid curve).

Considering the expected stability and reproducibility of PQRS complexes (Fatemian & D Hatzinakos 2009), amplitude statistics are computed around certain fiducial points, considering as outliers segments that present considerable deviations from the median statistics. The points chosen were (Figure 9):

- Time instant 75, approximately where the P wave is located;
- 150, just before the Q wave, where most of the signals show a small amplitude;
- 200, where the segments are centred – R peak;
- 300, just after the end of the repolarisation.

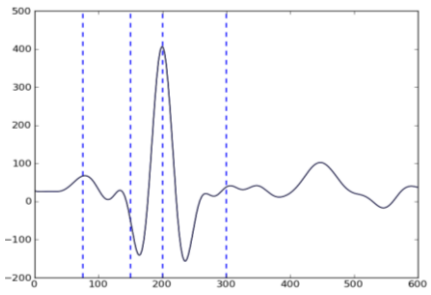


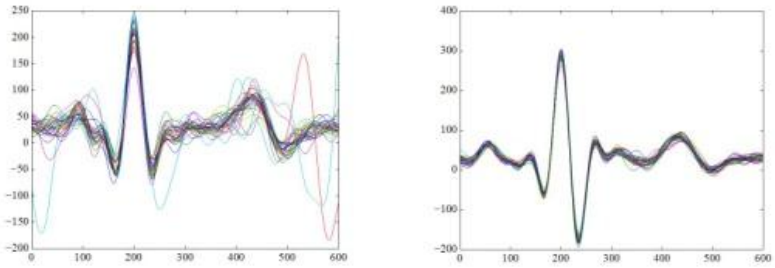
Figure 9. Typical ECG segment with the selected points for outlier removal.

Let *P* be set of points *p* mentioned before. Let *seg* be a segment of one individual ECG signal. Let *median* be the median in the point *p* for individual ID. The heuristic for outlier removal is the following:

$$
\begin{aligned}
&for\ \text{ID}\ in\ \text{population}: \\
&\quad for\ \text{p}\ in\ \text{P}: \\
&\quad\quad if\ |\text{seg[p]} - \text{median}| > |\text{median} \times \alpha| \\
&\quad\quad\quad then\ \text{seg} \rightarrow \text{outlier}
\end{aligned}
\tag{4}
$$

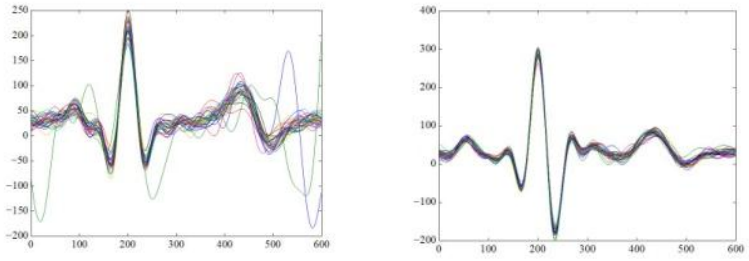
For each ECG recording of each individual, after signal segmentation, the median of signal amplitudes at each of the above fiducial points is computed; a segment within this set is considered an outlier (and further removed from the data set) if, at least at one of the fiducial points, the absolute difference between the amplitude value at the considered point and the corresponding median is larger than the median value multiplied by a factor α. The α parameter thus quantifies the distortion from the typical amplitude statistics; tuning of this parameter value was based on an empirical study, described in Chapter 4.

This heuristic is applied twice as can be seen in Figure 7. The results are pictured in Figure 10 and Figure 11.



(a) (b)

Figure 10. Segmented ECG after passing through the outlier removal heuristic once in subject *A* (noisy acquisition) (a) and in subject *B* (b) (clean acquisition)



(a) (b)

Figure 11. Segmented ECG after passing through the outlier removal heuristic twice in subject *A* (noisy acquisition) (a) and in subject *B* (b) (clean acquisition)

Note that this heuristic does not adapt individually to each heartbeat. The points are pre-defined and applied to every signal. However, this should not be limitative since (Fatemian & D Hatzinakos 2009) claim that the temporal length of the PQ segment and QRS complex is weakly dependent on the heart rate.

Outlier removal is part of the pre-processing phase for every data acquisition, both in enrolment and user identification phases. The outlier removal procedure is applied once or twice in sequence;

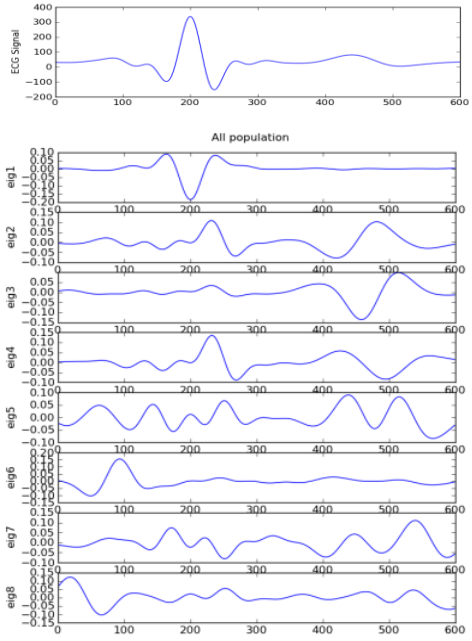
the corresponding remaining (clean) data after the one or two steps approach is hereafter referred as *DataF* and *DataFF*, respectively. Only two outlier removal iterations were used because it was verified that most of the individuals presented an apparently clean signal after the second iteration.

3.1.2 PCA-BASED FEATURE EXTRACTION

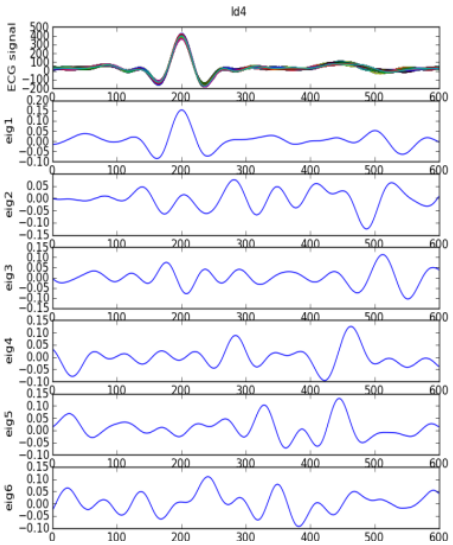
As a means for feature extraction and data representation, PCA is performed. By applying the PCA technique, as described in section 2.1.1, to the ECG data, each ECG segment is described as a linear combination of eigen-vectors, that will be referred to as *eigen-heartbeats*. By storing these eigen-heartbeats and the mean wave, each ECG segment is described by the set of coefficients in the linear combination, forming the set of features that describes it.

The PCA was explored in two different scenarios: (a) applied to the data of the whole population, leading to an eigen representation of the average pattern of ECG segments; (b) applied individually to each person's ECG segments.

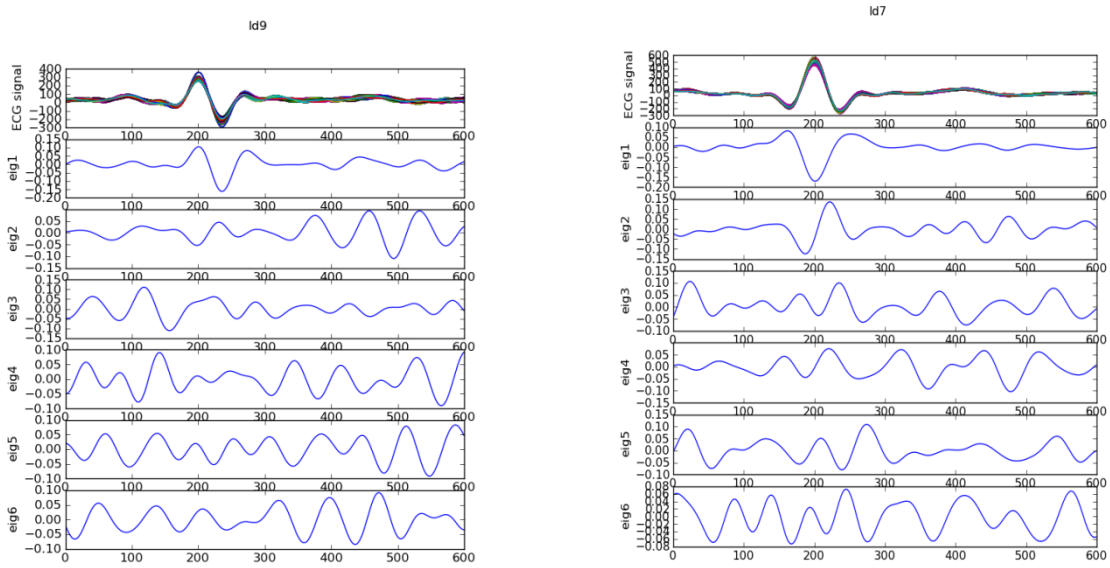
Figure 12 shows examples of eigen heartbeats produced with the different methods and also the different eigen-HB obtained for different individuals. Figure 12 (b) and (c) show how apparently equal ECG signals have clearly different eigen representations.



(a)



(b)



(c) (d)

Figure 12. (a) Overall population mean ECG signal and first 8 eigen-heartbeats obtained from all population's data (b), (c) and (d) Segmented ECG signal and first 6 eigen-heartbeats for three individuals.

Both of these methods will be further described in the next section.

3.1.3 CLASSIFICATION METHOD

Four classification perspectives were used. They all built in the same principle: applying PCA to the 600 points sample, i. e., an heartbeat (feature extraction and dimensionality reduction perspective), and using a k-Nearest Neighbours classifier for matching new data with template data. Figure 13 shows how PCA and K-NN get together to assemble the classifier.

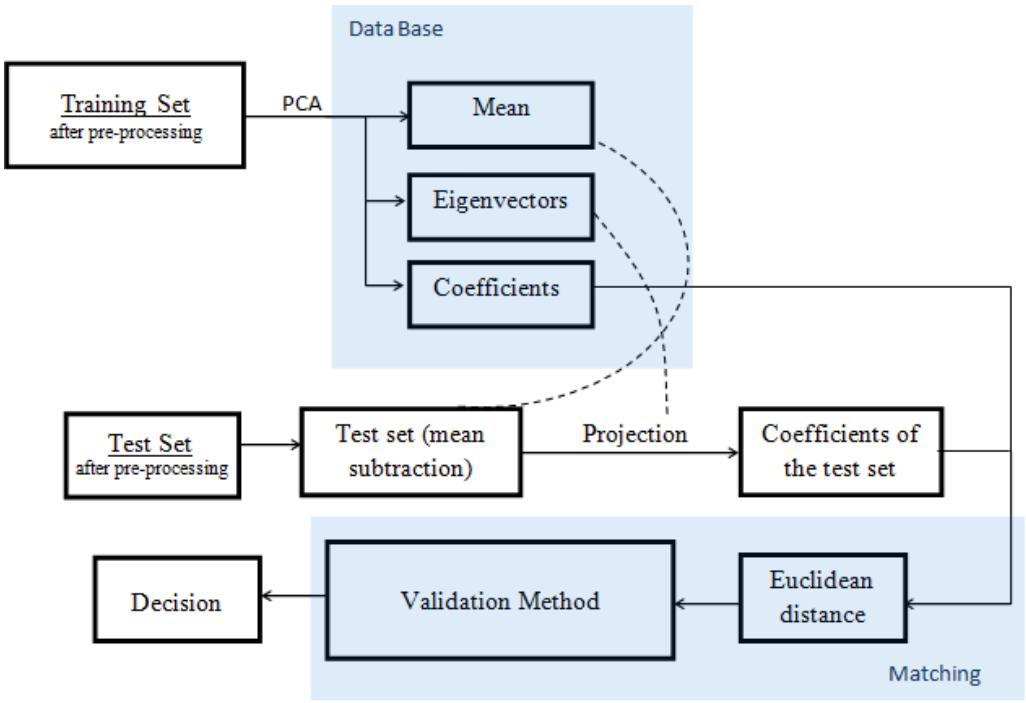


Figure 13. PCA and K-NN as classification step.

The training set is used for the creation of a database of templates. It corresponds to the enrolment step where the user will provide its ECG signal and his name. Generally, it can be said that the train set is composed by previously processed labelled data, i. e., classes. In this situation, a class is an individual. Train data is the pre-processed ECG; for generalization purposes, it is will be simple denoted as *sample*. The test set is pre-processed data of the same type as the training set, in this case, pre-processed new ECG acquisition; it corresponds to the identification/authentication step. The goal of classification is to assign a label to each test set, i. e., a name to each new user. Note that if no user has data similar enough (template distance under a certain threshold) the system can reject the person, i. e., don't assign a label to the new sample.

As explained in section 3.1.2, the PCA performed in the training set is applied in two perspectives: (a) applied to the data of all classes, resulting on an eigen representation of the average pattern of all the classes' samples; (b) applied individually to each class.

The first method, hereafter referred as the Overall Population Eigen-Biosignal (OEigBs) approach, leads to a database formed by the mean sample and eigenvectors corresponding to the all the classes' data (see Figure 14). Each training set group will be represented by the coefficients resulting from the projection of its samples into the database eigenvectors, and stored as a template for that class.

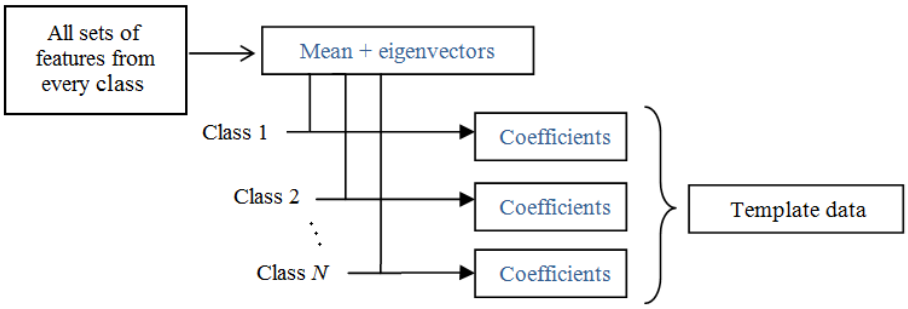


Figure 14. Database contents under the OEigBs approach.

The second method, hereafter referred as the Individualized Eigen-Biosignal (IEigBs) approach, will have, for each individual, as template, the mean sample, eigenvectors and coefficients corresponding to the projection of each sample into the individual eigen-signal. From each train set class those 3 components will be taken and stored in the database (see Figure 15).

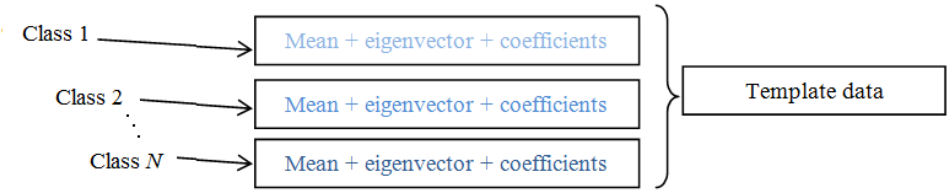


Figure 15. Database contents under the IEigBs approach.

3.1.4 DECISION

The decision section was divided in the two biometric perspectives mentioned before: identification and authentication. As explained, identification implies that a test set given to the system should be classified by comparison with every data base templates. Authentication requires that, along with the test data, a label is provided. That label will be validated by the system by comparing the database templates correspondent to that label and the new input data.

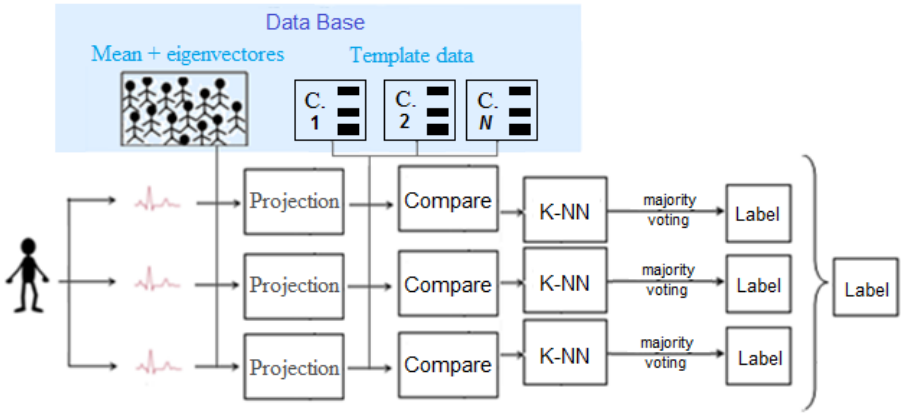
3.1.4.1 Identification methods

Identification is performed based on the comparison of the presented sample with the stored templates for each class used for training. The proposed decision algorithm is different for the OEigBs and IEigBs approaches.

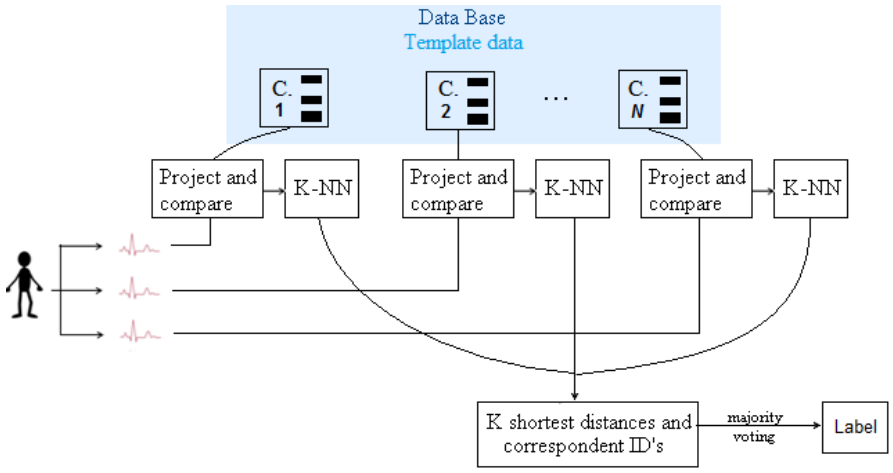
In the Overall Population Eigen-Biosignal identification process, the newly presented samples (after pre-processing) are projected into the eigenvectors taken from the whole population, i.e., taken from all the classes (see Figure 16(a)), and the feature vectors thus obtained are matched with the templates of train data. According to the Individualized Eigen-Biosignal identification approach, the new samples are projected into each data base eigen-signal, and these projection vectors are compared with the several classes' templates (see Figure 16(b)). Template matching uses the Euclidean distance and the K-Nearest Neighbours (K-NN) to associate each new data acquisition set with its most similar database template, along with the associated class label. The label of a given

sample is decided using a majority voting among the represented identities among the K-NN templates. When several test samples are used, the decision is accomplished using a majority voting over the overall k-NN templates. The number of templates stored for each class and the number of samples used for testing are parameters that influence the overall performance of the recognitions system, being experimentally evaluated in Chapter 4.

For system's performance evaluation, error rate is calculated by counting the number of times that the system fails to correctly label a class and dividing it by the number of tests done. Since the choice of training and test data is done randomly, several runs of each system's combination of parameters are made. The results presented in Chapter 4 are the mean and standard deviation obtained over the runs made.



(a)



(b)

Figure 16. (a) OEigBs and (b) IEigBs identification scheme. The *stickman* symbolizes the test input that is being identified (it can be an individual's biometric data, an individual's feeling a certain emotion or the individual belonging to a certain psychophysiological group). The red signal symbolizes the pre-processed biosignals (including feature extraction) from the individual.

3.1.4.2 Authentication methods

Train set will comprise each enrolling user's ECG segments and the test set will be composed by a new user's ECG segments. To do authentication, the algorithm receives the ECG signal of the person that is trying to be validated (test segment) and the identity (label) that the person claims to have (user name).

Also here, the two different PCA perspectives were used (OEigBs and IEigBs). In the OEigBs methods, the new segments will be projected onto the eigenvectors stored (referring to the whole dataset). The coefficients obtained will then be compared with the ones stored for the claimed identity (ID) (Figure 17). In the IEigBs perspective, the new segments will be projected onto the eigenvectors stored under the claimed ID. As a result, each new segment will be represented by coefficients, which will be compared with the ones stored for the claimed ID (Figure 18).

The comparison between test segments and templates is done using Euclidean distance. The new segment will be accepted as genuine if the Euclidean distance measured is under a certain threshold. When comparison is done using more than one segment, the decision is done using a majority voting scheme.

For system performance evaluation, ROC curves are created and the EER for each system's combination of parameters is found. Similarly to what happens in the identification method, the choice of training and test data is done randomly and several runs of each system's combination of parameters are made to avoid biased results. The results presented in Chapter 4 are the mean and standard deviation obtained over the runs made.

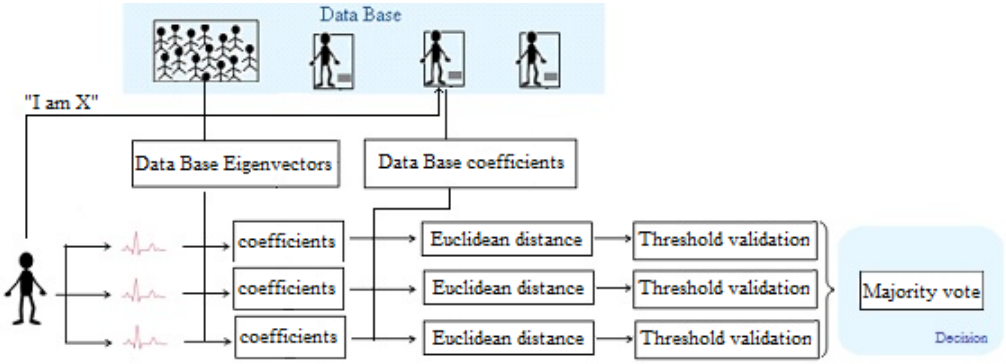


Figure 17. OEigBs authentication scheme.

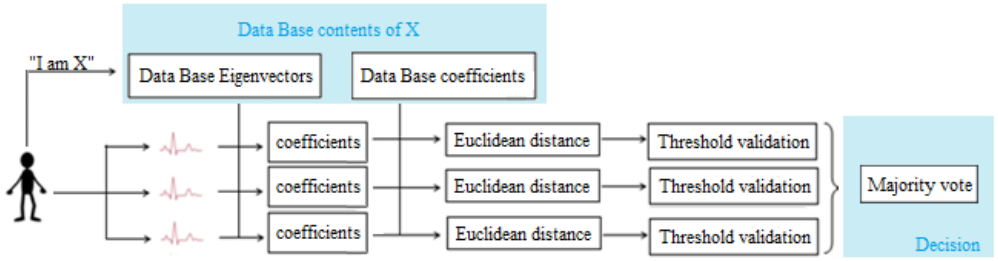


Figure 18. IEigBs authentication scheme.

3.2 PSYCHOPHYSIOLOGICAL DATA

The overall system for psychophysiological data analysis comprises a pipeline of modules, from data acquisition to classification, as summarized in Figure 19.

As referred before, for psychophysiological assessment three electrophysiological signals were studied: Blood Volume Pulse (BVP), Respiratory Signal (RESP) and Electro-dermal activity (EDA). These were acquired while the subject would watch a series of pictures chosen from the IAPS in a controlled environment. The pre-processing of these signals is rather different from the ECG. It comprises a filtering step, feature extraction and image-based segmentation.

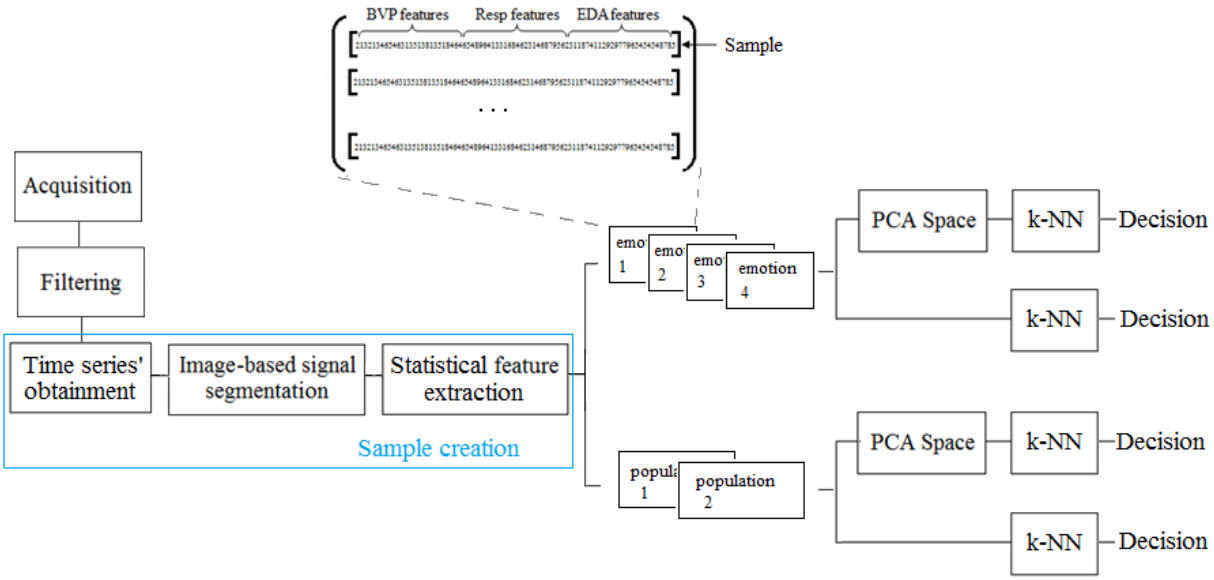


Figure 19. Methodology for psychophysiological data processing and analysis

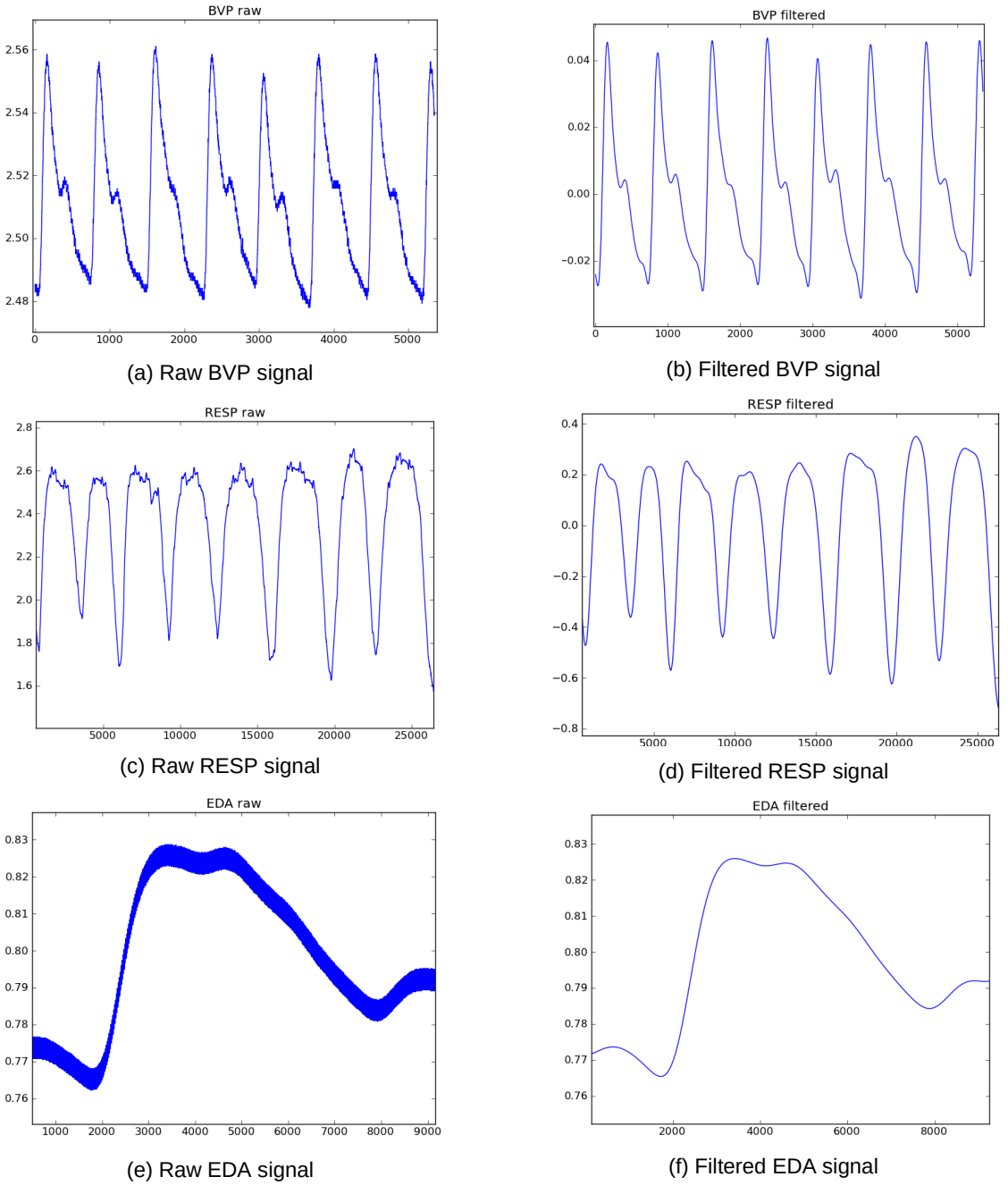
After the filtering, a series of step follow, constituting the sample creation step. A sample is an array that contains the features obtained from the signal acquired while one individual was watching one image. First, some time measurements are taken from the signal as a whole. After, image-based segmentation is performed (separating each individual's signals, and correspondent features, per image being watched) and finally statistical feature extraction is done over the segmented filtered signal and the segmented time measurements. All the features are normalized; for each feature, a minimum and a maximum value were found and used to scale all the values between zero and one.

The samples are then grouped by emotion elicited or by population group, depending on the type of analysis being performed, respectively emotion classification or group classification. Then, two classification approaches were used. In the first, the samples were mapped to the PCA space and classified with k-NN. In the second method, PCA was not used.

3.2.1 FILTERING

Inherent to every biosignal acquisition, there is some amount of noise due to factors such as powerline interference, motion, or baseline wander that needs to be filtered. Filtering thus constitutes the first step, following data acquisition. The EDA signal was filtered with a 2nd order Butterworth filter with an upper cut frequency of 1 Hz; Resp was filtered with a 2nd order Butterworth filter with an upper cut-off frequency of 1 Hz and a lower cut frequency of 0.1 Hz; and BVP was filtered with a 4nd order Butterworth filter with an upper cut frequency of 8 Hz and a lower cut frequency of 1 Hz.

Examples of raw and filtered signal of each signal are presented in Figure 20.



(a) Raw BVP signal

(b) Filtered BVP signal

(c) Raw RESP signal

(d) Filtered RESP signal

(e) Raw EDA signal

(f) Filtered EDA signal

Figure 20. Examples of BVP, RESP and EDA signals, as acquired and after filtering.

3.2.2 SAMPLE CREATION

During data acquisition the subjects were watching a sequence of images that triggered different emotions. A sample is composed by all the features extracted from one individual during the visualization of one image. The creation of the samples requires three steps shown in Figure 19: signal representation as a time series, signal segmentation and statistical feature extraction. The *Biosppy* toolbox is used (Canento et al. 2012) for time series analysis and statistical feature extraction. The following subsection gives an overview of the steps taken for sample creation.

3.2.2.1 Time series measures' obtainment

Time series measures are taken from the signal as a whole. It relates with the frequency / time stamp with which certain events occur in the signals. Each physiological signal has their specific features and therefore this section is further divided in the three signals studied.

3.2.2.1.1 Blood Volume Pulse (BVP)

From the BVP signal, the instantaneous Heart Rate (HR) and Inter Beat Interval (IBI) are measured. The heart rate gives the number of heart contractions per minute and is measured in *bpm* (beats per minute). IBI is measured in seconds and is the time interval between individual heart beats.

IBI and HR can be obtained through the formulas:

- IBI :

$$IBI(x) = t_{t+1}^{hb} - t_t^{hb}, t = 1, 2, \dots, Nb \tag{5}$$

- HR :

$$HR(x) = \frac{1}{Nb}\sum_{i=1}^{Nb}\frac{60.0}{IBI(i)} \tag{6}$$

where t_{t+1}^{hb} represents the time instant in seconds of the t[th] heart beat. *Nb* is the number of detected heart beats.

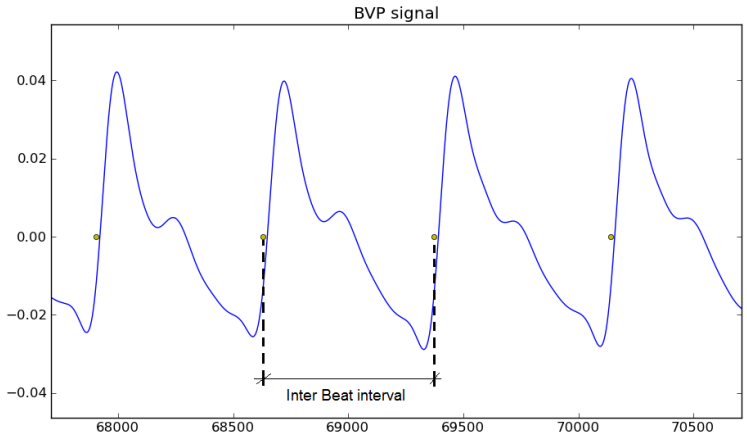


Figure 21. IBI in a filtered BVP signal

3.2.2.1.2 Respiratory signal

The instantaneous respiratory frequency (RF) is also measured. For that, the signal's zero crossings were detected. The inverse of the time between alternate zero crossing will give the RF.

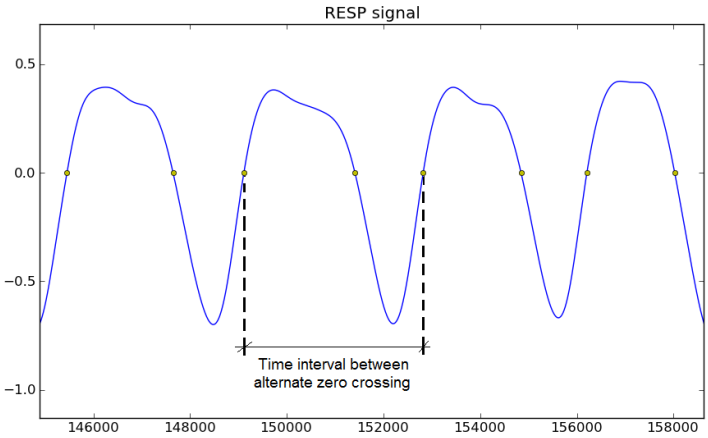


Figure 22. Time interval between alternate zero crossings in a filtered RESP signal

3.2.2.1.3 Electro Dermal Activity (EDA)

As described before, EDA has two main components – SCR (high frequency component) and SCL (low frequency component)

The method proposed by (H. Gamboa 2008) is used for SCR detection. It is based on the EDA's signal morphology and is capable of solving problems like low amplitude SCR detection. Assuming EDA's continuously differentiability, the derivative of signal is used for the calculus of several parameters and the SCR is seen as the output of a linear system with the input being the SCR triggering stimulus.

SCL is computed by filtering the signal using a Butterworth filter with an uppercut frequency of 0.05 Hz.

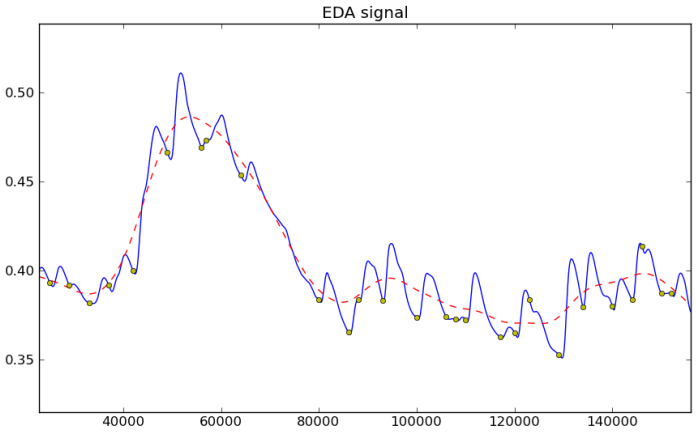


Figure 23. Filtered EDA (solid line), detection of the beginning of SCR events (dots) and SCL signal (dashed line)

3.2.2.2 Synchronization and Image-based Segmentation

Since a sample comprises the features extracted from the data acquired from one individual while he was watching one image, it is necessary to organize the acquired signals according to the image being watched. The synchronization between the computer screen, and correspondently the

images being showed, and the acquired physiological signals acquired is made by means of a light dependent resistor (LDR) sensor. Since a black screen was shown between the images, a clear square wave can be seen in the LDR signal when an image is shown, as depicted in Figure 24.

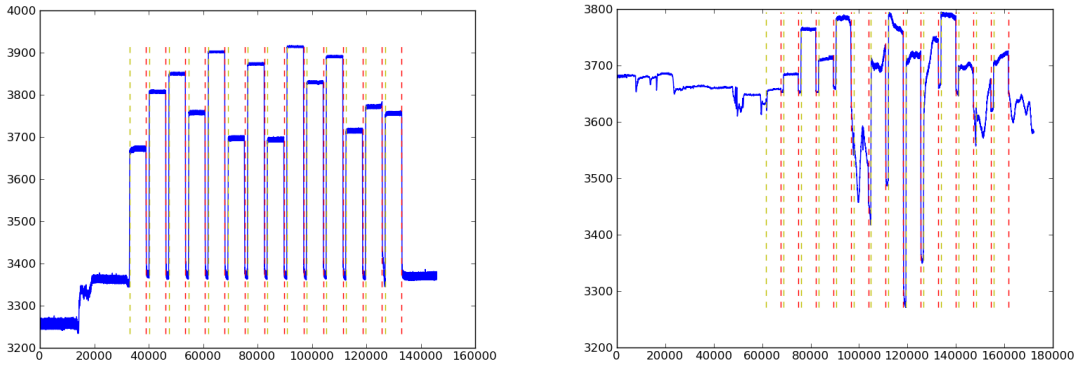


Figure 24. (a) Clean and (b) noisy LDR signal acquisition. The yellow and red lines mark the beginning and end of an image, respectively. The x-axis represents the time in milliseconds and y-axis the value measures by the LDR.

Using the LDR information, the filtered signal is segmented for statistical feature extraction (explained in the next section).

Associated with the time series measurements, an *onset* array was also obtained from the signals. It contains the absolute time instant associated with the measurements. That array was used to make the correspondence between the time measures and the image during which the signal was acquired.

In the BVP signal there are several events between the beginning and the end of the picture visualization, so the measurements associated with each image are the ones that occur during the image visualization period of time.

Since the respiratory cycle's length is approximately 5 seconds and the image visualization had a 6 seconds length, sometimes only a respiratory cycle happened during an image observation and other times the picture visualization would occur between the end of one cycle and the beginning of another. In the latest case, the measurement extracted is a linear interpolation between the feature value of the cycle that is ending and the cycle that is beginning.

For the EDA case, some of the times there would be no SCR event starting during the image visualization time. In this situation, the SCR amplitude value would be zero. On the other hand, SCL measurement is always possible since it does not rely on events of the signal. No *onset* array was needed, it is obtained by segmented the SCL signal obtained by signal filtering.

3.2.2.3 Statistical Feature extraction

Two types of features are extracted: statistical features taken the segmented filtered signal and statistical features taken from the time series obtained previously to the segmentation.

The features extracted from the filtered signal are common to every signal. Those features do not depend on the type of signal as they don't depend on the events occurring in the signals. The

computing of these variables is only dependent on the absolute values that represent the signal in a period of time. The defined features are:

- Mean:

$$u(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{7}$$

- Variance:

$$\sigma^2(x) = \frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^2 \tag{8}$$

- Absolute Deviation (AD):

$$AD\ (x) = \frac{1}{N}\sum_{i=1}^{N} |x_i - u(x)| \tag{9}$$

- Standard Deviation (SD):

$$\sigma\ (x) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^2} \tag{10}$$

- Skewness:

$$Skewness\ (x) = \frac{\frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^{3^{3/2}}}{\frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^2} \tag{11}$$

- Kurtosis:

$$Kurtosis\ (x) = \frac{\frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^{4^2}}{\frac{1}{N}\sum_{i=1}^{N} (x_i - u(x))^2} - 3 \tag{12}$$

where *x* is the signal, x_i is the i^{th} sample of time series *x*, and *N* is the number of samples.

Standard deviation and variance evaluate the level of dispersion of the data from its mean. Absolute deviation is the mean of the distance of every point to the mean.

Skewness and Kurtosis are measures that characterize the general shape of the signal. Skewness is a measure of symmetry, more specifically, the lack of symmetry. It evaluates how similar are the left and right sides of the signal. Kurtosis measures how peaked the data is when compared to a normal distribution. The lower the kurtosis value, the flatter the signal.

Regarding the statistical treatment of the time series measurements, different features are taken according to the signal. For the BVP signal, HR and IBI mean and SD are calculated as described in formulas (7) and (10), respectively. From the RESP signal, the mean of the RF is taken in case that

more than one respiratory cycle occurs; if only one cycle is registered, its value is used as feature. In the EDA signal, the amplitude (or mean amplitude, in the case that more than one event is detected) of the detected SCR events is used as feature; if no event is detected the amplitude is set to 0. For the SCL measurement, mean value, standard deviation and variance are computed using the formulas (5), (8) and (6), respectively.

3.2.3 CLASSIFICATION

As shown in Figure 19, after sample creation, samples are separated by emotion type and by population group, resulting in two different analyses of the data: *emotions classification* and *population group classification*. However, the classification method is similar in both situations.

3.2.3.1 Emotion Classification

Emotions' classification is done using the same line of thought as individuals' classification. This time, each class is a different emotion, and instead of representing them by several heartbeats, emotions are represented by samples.

Emotion classification is done within each population group. For example, in the Experimental Group each emotion has 123 events (41 EG individuals times 3 emotion eliciting images). For each emotion, the samples was randomly split into test data and training data.

3.2.3.2 Population group classification

Here, the procedure is similar to the one described in the previous section; however, after feature extraction, the features are grouped by population type instead of emotion type. The classification method is evaluated using the samples corresponding to only one emotion and to all emotions indiscriminately.

3.2.3.3 Template creation and decision process

After grouping the samples in classes (emotions or population group, see Figure 19), two tests are performed. The first uses PCA to map the sets of features to a new representation space, followed by an Euclidean distance based k-NN classification; the second does not use PCA, the Euclidean distance is measured directly from the set of features of each sample and k-NN method is used for classification.

Regarding the method using PCA, for psychophysiological analysis the IEigBs and OEigBs methods are used in only in an "identification" perspective, i. e., the new samples are presented to the system for classification without a label (that could be validated or not). The reason for that is that psychophysiological data has considerable fewer groups to be classified and in a practical application it might be more useful to identify then to validate psychophysiological states.

For training, a number of samples are randomly chosen from each class and the rest are used for testing. Each population group classification is further divided in two testing perspectives. The first, assumes that all the individuals inside one population group have the same physiological characteristics, i. e., test sets are composed by samples belonging to random individuals. The second

perspective is closer to a real situation; the samples left for testing are sorted so that each test set is composed by samples from the same individual.

Classification is performed as described in section 3.1.4.1.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

The last step of a classifier design is to evaluate its performance. The results of applying the proposed methodology to real data sets are presented and discussed in this section. This section will be divided in the two analyses issued, biometric and psychophysiological. In both subsections the dataset will firstly be described, followed by sections in which the influence of several design parameters on the overall accuracy of the classification system will be evaluated. These include classification error rates as a function of the number of sets of features *(NS)* used as templates in the data base creation phase, the number of sets of features used when trying to access the system *(k)*, and the number of Nearest Neighbours (K-NN) used in the decision process. In the biometric analysis case, it will also be studied the influence of the α-value in the outlier removal procedure.

4.1 BIOMETRIC ANALYSIS

4.1.1 DATASET

The ECG datasets used in this experimental evaluation were provided by the *Check Your Biosignals Here* initiative (H. Silva et al. 2011). The dataset comprises a one session of acquisition of different physiological signals, including the ECG, over a population of 65 volunteering individuals, in an environmentally unconstrained setup. The experiment consisted of two distinct moments: an introductory phase, during which the user was explained the goal and details of the experiment; an emotion inducing phase triggered by the visualization a video sequence. The acquisition time was thus variable, depending on the duration of the interaction between the user and the staff element that

performed the verbal explanation of the test. ECG signals were collected from fingers and palms using dry Ag/AgCl electrodes. Intra-subject variability is only partially studied in this work. The video sequence presented triggered different emotions, so the acquired signal includes some emotional related variability, however, for each user only a single acquisition in done not allowing the study of heartbeat variability through time.

4.1.2 OUTLIER REMOVAL PROCEDURE

Due to variable acquisition times, for different individuals the total number of segments varies. Also, there are a different number of outliers for each individual due to different user reaction that led to movements and other types of artefacts. As a result, the α-value, that controls the level of outlier removal, will lead to different number of segments being kept per user. Figure 25 and Figure 26 show how the total number of segments kept varies with the α-value for each individual.

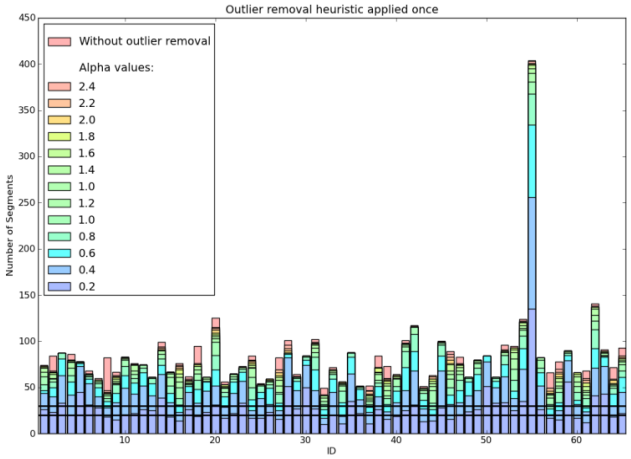


Figure 25. Number of segments, per user, for different α-values after applying the outlier removal procedure once. Two horizontal black lines mark a 20 and 30 segments minimum limit.

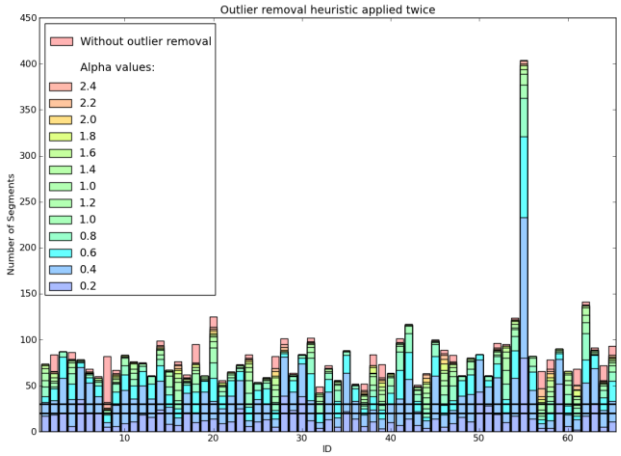
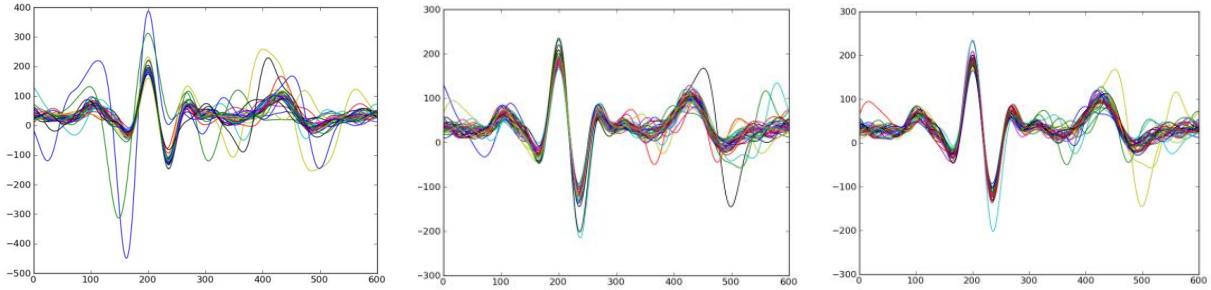


Figure 26. Number of segments, per user, for different α-values after applying the outlier removal procedure twice.

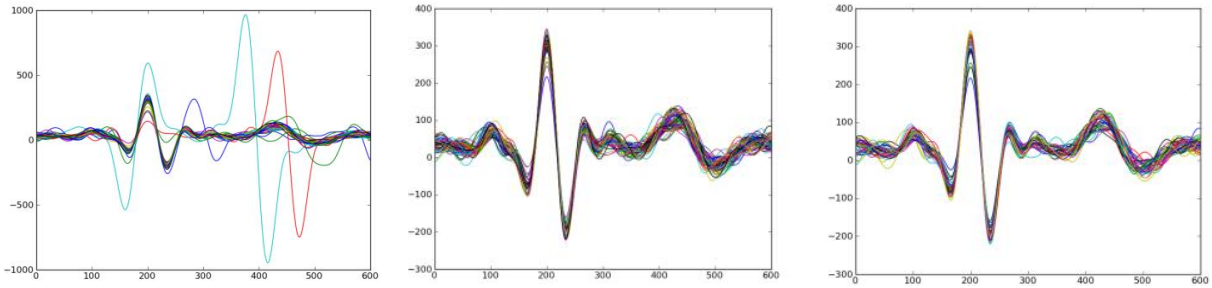
In Figure 25 and Figure 26 one can see that the amount of segments being removed varies from user to user. Individual 8, for instance, exhibits a very large percentage of outliers being removed. Figure 27 shows the ECG segments from that individual, where one can see that he had, in fact, a large amount of outliers that the outlier removal procedure eliminated almost completely.



(a) (b) (c)

Figure 27. Individual 8 segmented HB's with no outlier removal (a), passing through the outlier removal procedure once (b) and twice (c), with α =0,4.

One the other hand, ID 30 has a lower fraction of removed segments. In Figure 28, one can see that the amount of outliers was smaller and successfully removed.



(a) (b) (c)

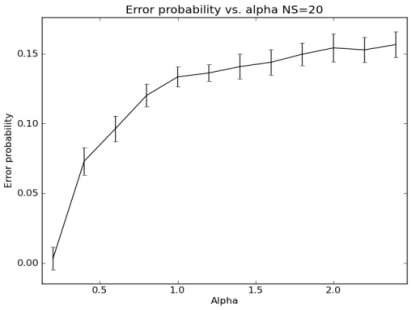
Figure 28. Individual 30 segmented HB's with no outlier removal (a), passing through the outlier removal procedure once (b) and twice (c), with α =0,4.

To standardize the number of segments (number of samples - *NS*) used as templates per individual, the *NS* kept in the enrolment phase is made constant. Two values are tested: 20 and 30. In order to evaluate the error probability of the identification system, independent training and test sets are used, randomly chosen from the available data. *NS* segments are chosen for training, and the remaining segments per individual, after outlier removal, are used to assess the identification accuracy (test data). Error estimates are performed by averaging over 25 runs of the classification procedure using randomly selected training and test sets. However, for some individuals and α-values combinations, the minimum *NS* established is not reached. Those are counted as individuals that "failed to enrol" (FTE). The FTE statistics are shown Table 2, as a function of the α-parameter.

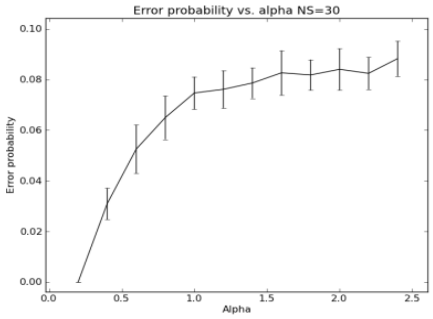
Table 2. Failure to enrol rates as a function of the alpha value for the different types of data (DataF and DataFF), with different number of segments as templates, NS.

	DataF		**DataFF**	
alfa \ NS	*20*	*30*	*20*	*30*
0,2	0,3384	0,7230	0,7538	0,8923
0,4	0,0307	0,2153	0,2153	0,3538
0,6	0	0,0769	0,0615	0,2
0,8	0	0	0,0153	0,0923
1,0	0	0	0	0,0461
1,2	0	0	0	0,0153
1,4	0	0	0	0,0153
1,6	0	0	0	0,0153
1,8	0	0	0	0,0153
2,0	0	0	0	0,0153
2,2	0	0	0	0,0153
2,4	0	0	0	0

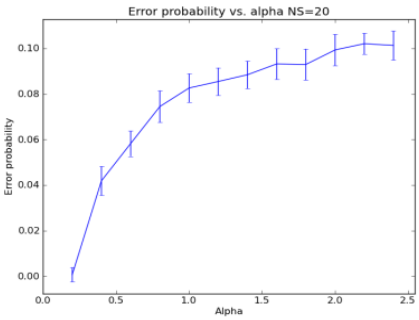
The value of α will also influence the identification rates obtained. The larger the value of α, the higher the number of segments that are kept, leading to a smaller “failure to enrol” rate (FTE); however, with the corresponding larger amount of outliers left in the data with these larger α values, larger identification error rates are obtained. This effect is clearly shown in Figure 29 (a) to (h).



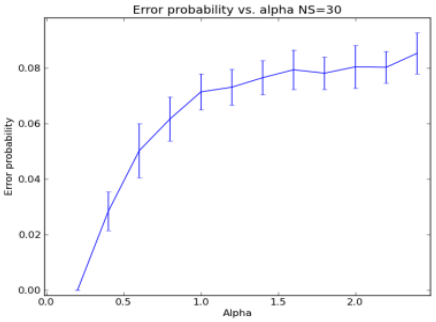
(a)



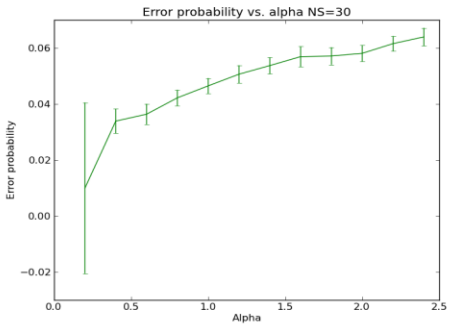
(b)



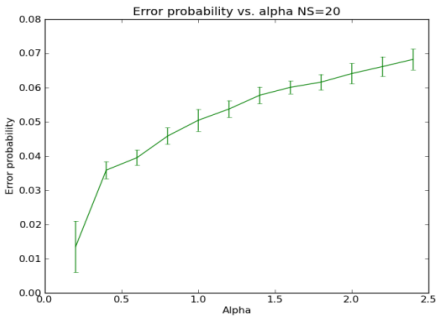
(c)



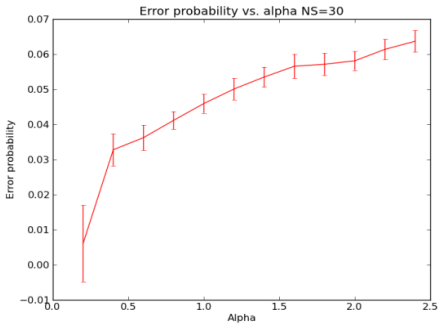
(d)



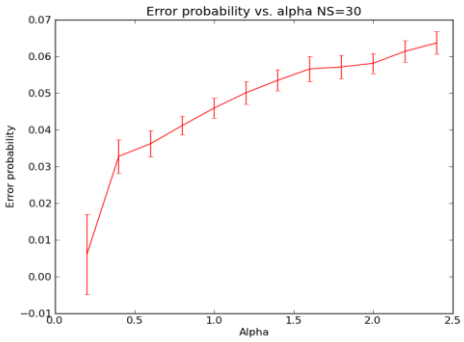
(e)



(f)



(g)



(h)

Figure 29. Error probability mean and standard deviation variation with the α value for the different identification methods after 25 runs, with dataFF, using k=3, K-NN=3 and: (a) IEigBs identification and NS=20; (b) IEigBs identification and NS=30; (c) OEigBs identification and NS=20; (d) OEigBs identification and NS=30; (e) IEigBs authentication and NS=20; (f) IEigBs authentication and NS=30; (g) OEigBs authentication and NS=20; (h) OEigBs authentication and NS=30. Each point corresponds to a different α-value in a range from 0,2 to 2,4.

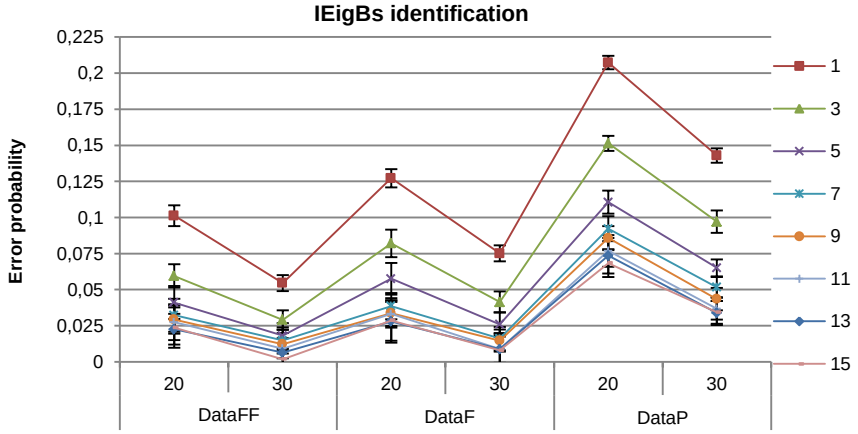
Considering the two identification methods, IEigBs and OEigBs, the lowest identification error rates, with acceptable FTE rates, are obtained using the outlier removal procedure with α = 0,4. However, for large values of *NS* and number of segments required for entering the system (*k*), it is possible to obtain similar identification errors with lower FTE errors. In order to use the same parameter value for all individuals, the α = 0.40 value is, ultimately, chosen, and used hereafter in the subsequent studies.

4.1.3 NUMBER OF SAMPLES FOR ENROLMENT *(NS)*

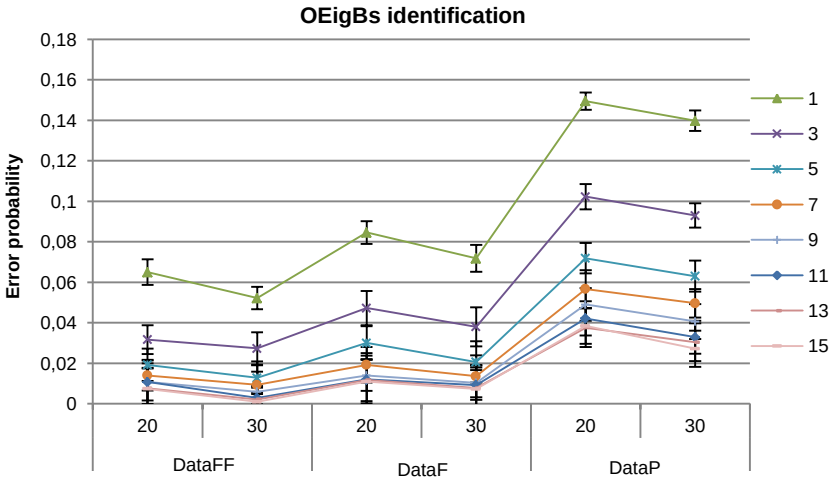
In this section the influence of the number of templates per user used on the identification accuracy of the system is evaluated. As referred before, in order to perform the tests on the available data, *NS* segments as templates (training data) are randomly selected and the remaining segments are used for performance evaluation (test data). This procedure is repeated 25 times. Results are presented in the next plot showing average and standard deviation results of the identification error rates using a 1-NN classifier and different values for k, the number of ECG segments presented for accessing the system. Tested situations include NS=20 and NS=30 for the three setups of: no outlier

removal (dataP); outlier removal in one step (dataF); and using twice the outlier removal procedure (dataFF). Figure 30 (a) concerns the Individualized Eigen- Biosignal (IEigBs) identification, Figure 30 (b) corresponds to the Overall Population Eigen-Biosignal (OEigBs) identification, Figure 30 (c) corresponds to the Individualized Population Eigen- Biosignal (IEigBs) authentication, and Figure 30 (d) refers to the Overall Population Eigen- Biosignal (OEigBs) authentication

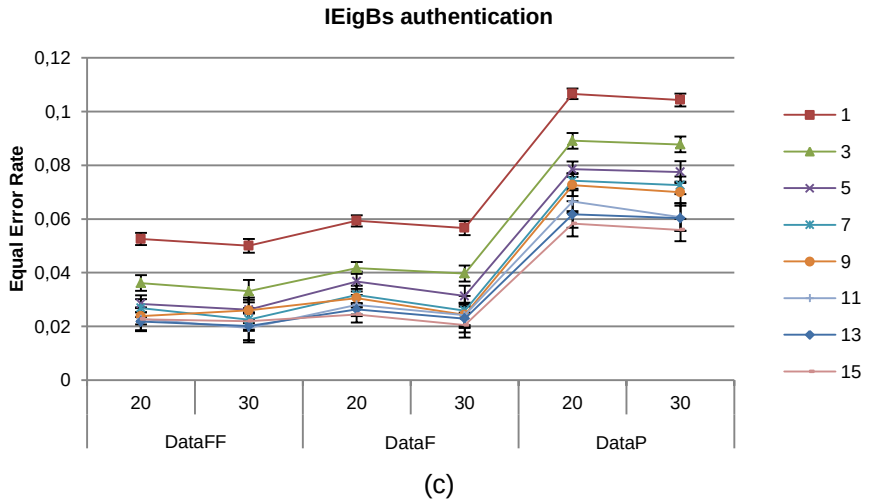
As shown, the higher the *NS* the lower the error probability is, and so longer enrolment times are preferable. With more template segments, they better capture the variability of the subject's HB so new segments are more likely to mach correctly the ones of the database. The OEigBs approaches seem to be less sensitive to the various configurations, having lower ranges on the error rates than the IEigBs approaches. Identification methods apparent to be more sensitive to the *NS* then authentication methods, where the error value difference between NS=20 and NS=30 is less evident.



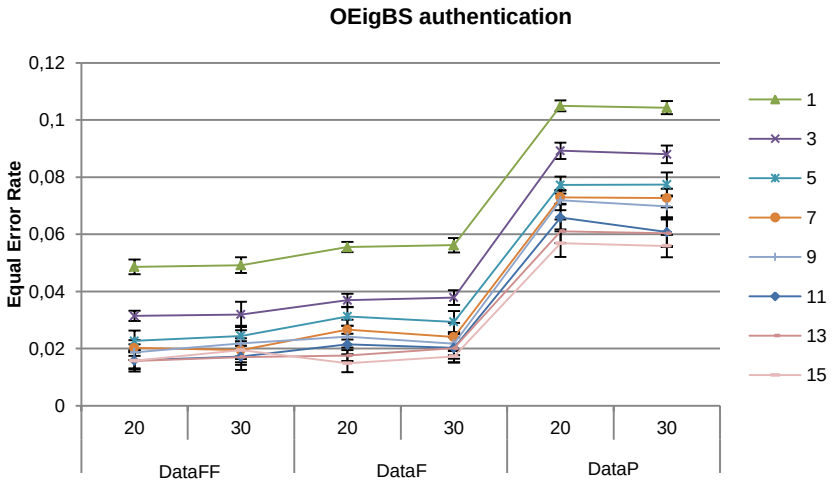
(a)



(b)



(c)



(d)

Figure 30. IEigBs identification; (b) OEigBs identification; (c) IEigBs authentication; (d) OEigBs authentication. Both identification plots refer to the identification error obtained with 1-NN. In all the plots, the energy is set to 1.Each line represents the number of segments, k, required for accessing the system. In the x-axis the number of segments kept in the data base and the data type used are represented (refer to Figure 7 in Chapter 3).

4.1.4 NUMBER OF SAMPLES REQUIRED FOR ENTERING THE SYSTEM *(K)*

The number of samples or segments required for entering the system is closely related with the acquisition time when trying to identify a subject in the recognition phase. It is the number of heartbeats that the user provides to the system in order to be identified.

From Figure 30, and similarly to the *NS* study, also for this parameter the larger the amount of segments, k, the lower the error probability. However the gain appears to have a lower bound. Values of *k* between 9 and 15 lead to similar error probability. For large values of *k* and *NS* it can be observed a 0% error probability for the identification methods, while for authentication methods 1.9% equal error rate is verified.

Note that identification and authentication errors have very different calculation methods and different meaning. The identification error is computed as the number of wrong recognitions over the total number of recognition tests made; concerning user authentication, system performance is summarised as the equal error rate obtained from the ROC curve.

The higher error in IEigBs can be explained by the number of segments used for training the system. For this method one has individual recognition systems trained with *NS* segments while for OEigBs the number of segments used for training the system is *NS* times the number of individuals.

4.1.5 OUTLIER SENSIBILITY

From Figure 30 it is apparent that the identification and authentication error decreases with the decrease of the number of outliers among the data (compare results with and without outlier removal). Therefore, there is a clear benefit from putting the data through an outlier removal procedure. However, the gain is not so impressive for the second time one applies the procedure – DataFF results.

All the methods (OEigBs identification and authentication and IEigBs identification and authentication) lead to error probabilities lower than 6% without outlier removal (DataP) if *NS* and *k* are big enough. However, with DataFF, identification approach can achieve an error probability very close to zero, and with a small variance. The authentication approach seems to be less sensible to outliers, since it does not reach errors as high as the identification approach for small *k* values and no outlier removal. Also, in the authentication approach, error standard deviation values are consistently smaller

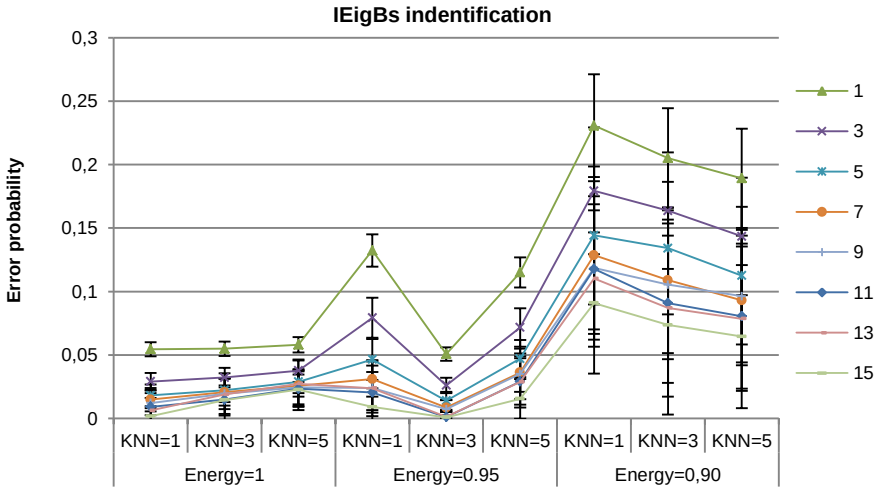
4.1.6 ENERGY

The use of PCA for data compression is based on the fact that not every eigenvector coming from applying PCA to original signal needs to be used for an acceptable signal reconstruction. The reduction of the data energy is associated with a compression of the data that is obtained by eliminating some eigenvectors. The eigenvectors with lower corresponding eigenvalues express a very low variance of data; so, by eliminating those eigenvectors, one can compress data a lot although there is a low reduction on the energy. For the particular case of data reduction in these database's ECG signals, the relation of compression level and energy reduction in explicit in Table 3.

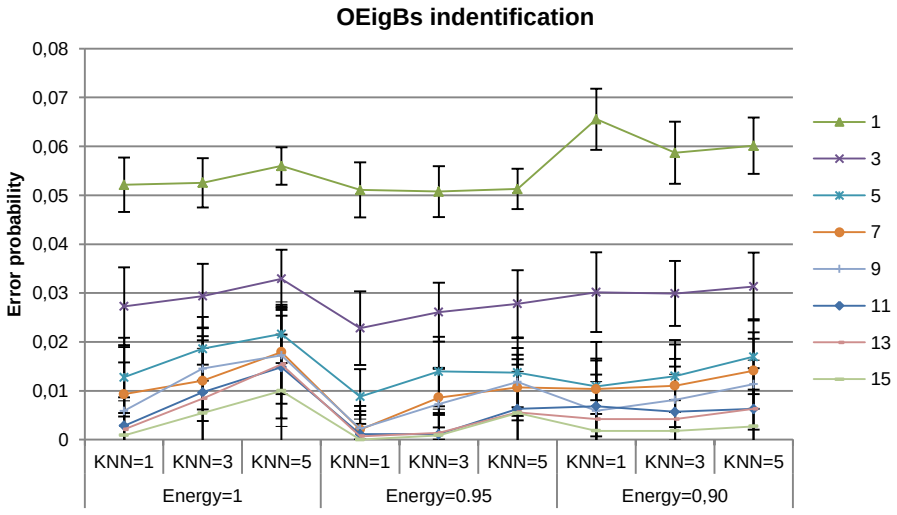
Table 3. Average compression level of the different data types for different energies.

	DataFF		**DataF**		**DataP**	
Energy \ NS	***20***	***30***	***20***	***30***	***20***	***30***
1,00	0	0	0	0	0	0
0,95	0,4	0,51	0,44	0,54	0,52	0,62
0,90	0,53	0,63	0,55	0,64	0,62	0,71

Figure 31 and Figure 32 plot authentication and identification errors for different scenarios with different compression levels. The Overall Population Eigen-Biosignal approach is the one that most benefits from data compressing, keeping both the mean and standard deviation similar or smaller with the decrease of the data energy. OEigBs authentication stands out for a relatively big decrease in the error. With 90% data energy, an error of 0.3% is obtained for DataFF and *k=15*. On the other hand, for the Individualized Eigen-Biosignal method, both the mean and standard deviation is similar or increases for lower energy values.



(a)



(b)

Figure 31. Error probability variation in IEigBs and OEigBs identification methods, with DataFF and NS=30, for different energy and K-NN values.

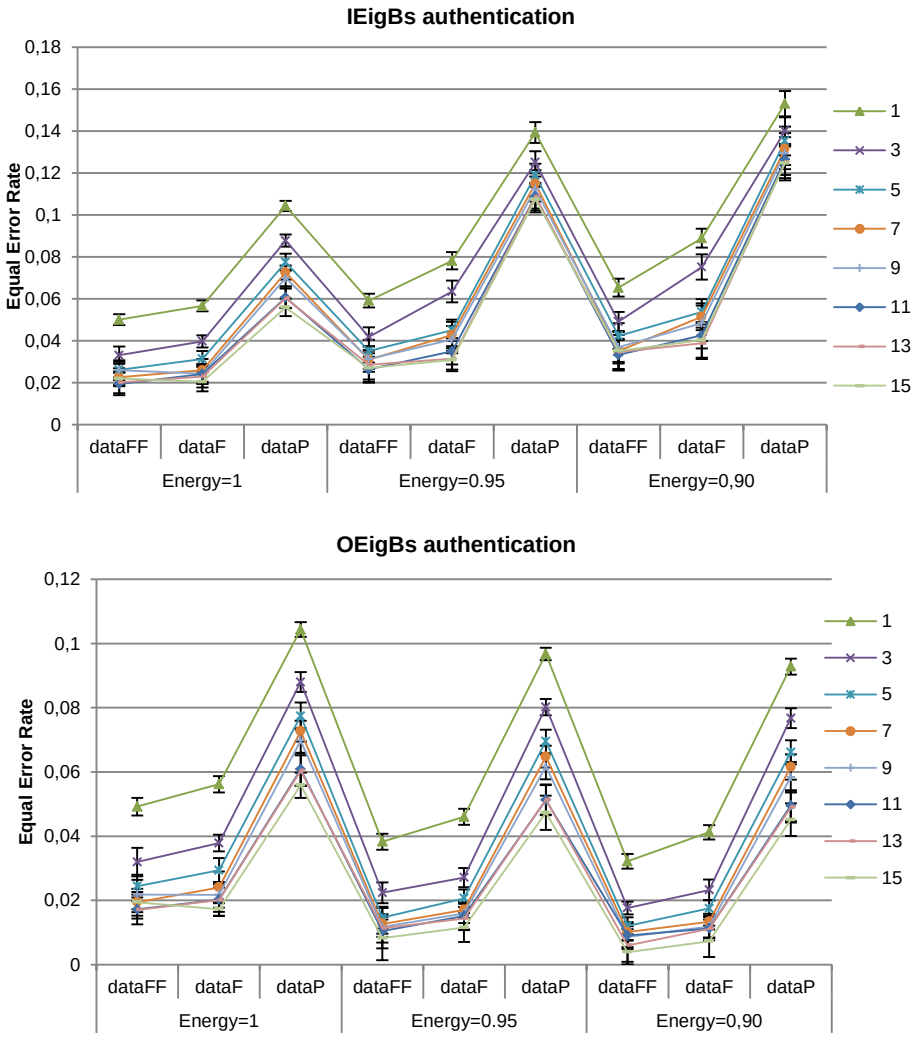


Figure 32. Error probability variation in IEigBs and OEigBs authentication methods, for the 3 types of data and with NS=30, for different energy values.

4.1.7 K- NEAREST NEIGHBOURS (K-NN)

Evaluation of the k-nearest neigbours used for classification is only applicable to indentification methods, since in authentication methods evaluation is made by finding the equal error rate. As depicted in Figure 31, the number of K-Nearest Neighbors used in the decision method does not seem to influence significantly the error probability's mean. However, there is a general tendency that for lower energys and low values of k, the better results are obtained by increasing the K-NN. This indicates that when the data is poorer (less segments, less energy) it is advisable to use a higher number of neighbours in the decision process in order to lower the identification error.

4.2 PSYCHOPHYSIOLOGICAL ANALYSIS

4.2.1 DATASET

Data was collected by researchers from the Faculdade de Medicina de Lisboa (Torrado, M. & Ouakinin 2011), in the scope of study on psychophysiological behaviour on subjects with a history of drug abuse, when exposed to emotion-eliciting stimuli. Three different physiological signals were collected: Blood Volume Pulse (BVP), Respiratory (RESP) and electrical dermal activity (EDA). A bioPLUX research wireless biosignal acquisition unit was used for data acquisition, enabling synchronous sampling and real-time transmission of the collected data to a base station; raw sensor data was acquired with 1000Hz sampling rate and 12-bit resolution. During the acquisition, the subjects watched a sequence of pictures previously chosen from the IAPS database (P.J. Lang et al. 1997). The sequence was composed by 14 images that were meant to elicit different emotions. Table 4 specifies which IAPS images were used. Each image was shown for 6 seconds, followed by a 1 second black screen. The synchronization between the computer screen, and correspondently, the images being showed and the acquired physiological signals was made by means of a LDR sensor.

In this experiment, the emotions are represented in a valence-arousal space, i. e., the images are characterized with typical valence and arousal values. The valence and arousal values assigned to each picture in Table 4, were obtained by (P.J. Lang et al. 1997) in a experiment where several young subjects were asked to rate the images in terms of valence and arousal in a scale from 1 to 9, being 1 a low rating and 9 a high rating. Four emotion groups are distinguished: positive valence and arousal (++), negative valence and arousal (--), positive valence and negative arousal (+-) and negative valence and positive arousal (-+).

Table 4. IAPS reference of the pictures visualized and their valence and arousal values.

Nr. in Sequence	**IAPS nr.**	**Valence** [Mean (SD)]		**Arousal** [Mean (SD)]	
1	1070	3.96 (2.30)	-	6.16 (2.08)	+
2	1650	6.65 (2.25)	+	6.23 (1.99)	+
3	1932	3.85 (2.11)	-	6.47 (2.20)	+
4	2039	3.65 (1.44)	-	3.46 (1.94)	-
5	2206	4.06 (1.40)	-	3.71 (2.03)	-
6	2312	3.71 (1.64)	-	4.02 (1.66)	-
7	3069	1.70 (1.41)	-	7.03 (2.41)	+
8	4660	(F)* 7.22 (1.40)	+	6.31 (1.95)	+
8	4668	(M)* 6.67 (1.69)	+	7.13 (1.62)	+
9	5760	8.05 (1.23)	+	3.22 (2.39)	-
10	5781	7.13 (1.49)	+	3.82 (2.37)	-
11	5891	7.22 (1.46)	+	3.29 (2.57)	-

12	8185	7.57 (1.52)	+	7.27 (2.08)	+
13	9410	1.51 (1.15)	-	7.07 (2.06)	+
14	9940	1.62 (1.20)	-	7.15 (2.24)	+

* Images were differentiated according to the subject (female or male)

Each emotion group have three image sequences, except for the -+ emotion, to which five images are correspondent. To guarantee unbiased results, only three of the five -+ images are chosen. The images chosen are the ones with lower valence value, since the group's valence is meant to be negative, and higher arousal value, since the group's arousal should be positive. Hence, images 1 and 3 are excluded from the tests.

The database comprises acquisitions under the described protocol taken from 45 patients with a drug abuse record, the experimental group (EG), and 26 control subjects, the control group (CG). However, due to errors in the acquisition process, only 41 EG and 22 CG acquisitions are used. This dataset is thus unbalanced. To avoid biased classification, random under sampling is applied to the EG group, i. e., random samples are eliminated from the EG group. To try to avoid discarding important information from the EG group several runs of the classifier are done. The error values presented in the following section are a mean and a standard deviation of the error values obtained over 30 runs.

The subjects belonging to the experimental group have ages ranging from 19 to 59 years old (mean: 40.29, SD: 8.495) that majorly consumed Cocaine and Cannabis/Hashish or a combination of both substances. Subjects from the control group have ages ranging from 23 to 66 years olds (mean: 36.17; SD: 12.135).

4.2.2 FIDUCIAL METHOD USING PCA FOR DATA REPRESENTATION

As explained before, fiducial feature extraction is used for psychophysiological classification. Table 5 summarizes the features extracted from the different physiological signals.

Table 5. Summary of the features extracted from the different signals

Feature type	BVP	RESP	EDA
Features obtained from the time series measurements	Heart Rate mean and standard deviation	Respiratory frequency mean	SCR amplitude mean
	Inter Beat Interval mean and standard deviation		SCL mean, standard deviation and variation

Features obtained from the statistic treatment of the signal	Absolute Deviation Variance Mean Kurtosis Skew Standard Deviation

4.2.2.1 Emotion classification

After trying different configurations of the classifier (*NS*, *k*, etc), an average 75% error rate obtained for the classification of the four emotions, which suggests that the emotions were not separable based on those features.

Tests were also made with only some feature types or only some of the emotions, but the results were similar.

These results obliged to further investigation. The histograms in Figure 33 show the distance between same emotion features (purple) and different emotion features (green). It is possible to see that the distances overlap, leading to the conclusion that emotions cannot be separated using the features mentioned.

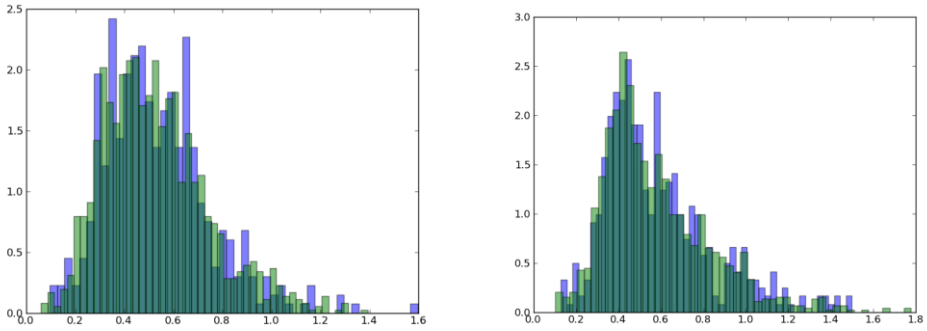


Figure 33. Distance between same emotion features (purple) and different emotion features (green) for the two identification methods

Figure 35 shows the normalized values of the 27 features obtained and Figure 36 shows the feature values in the PCA space. Each colour represents feature values belonging to one emotion. The features as they are represented in the features' axis are schematized in Figure 34. Again, there is no evident way to separate the emotions in neither of the spaces. This can be due to the emotion elicitation protocol. It was a passive elicitation in not fully controlled environment. Some distractions might occur, like noise coming from the outside, and the subject might not be always fully concentrated in the image being watched.

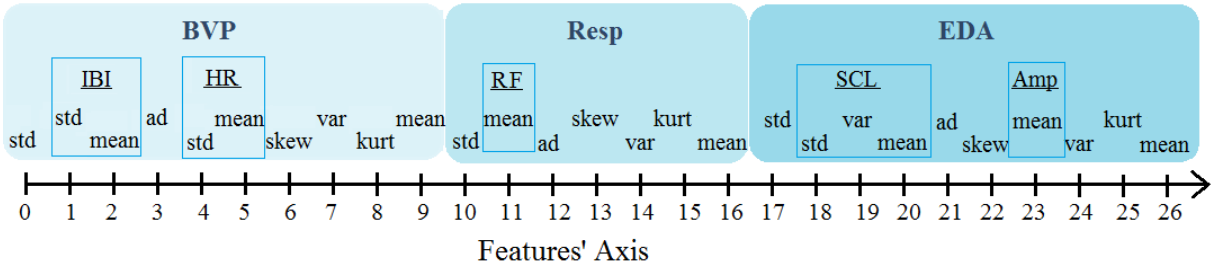


Figure 34. Features' order in the set of features. Features coming from the time series measures are framed.

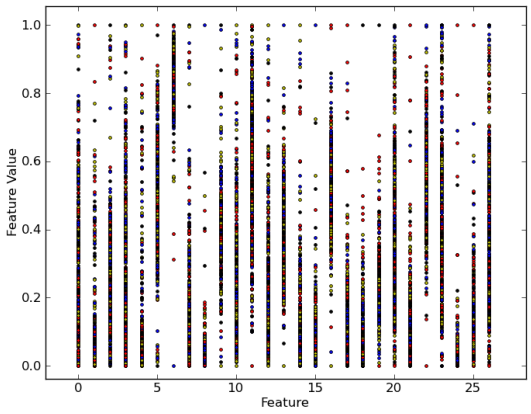


Figure 35. Feature value's distribution

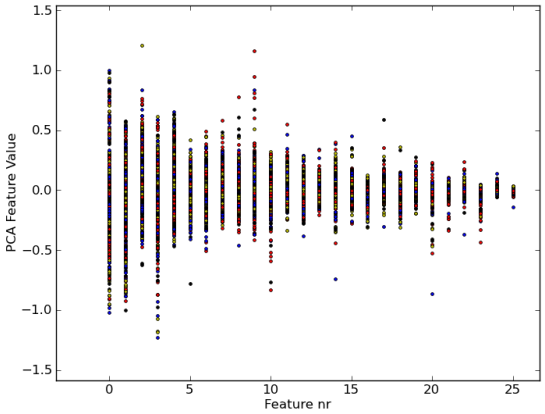
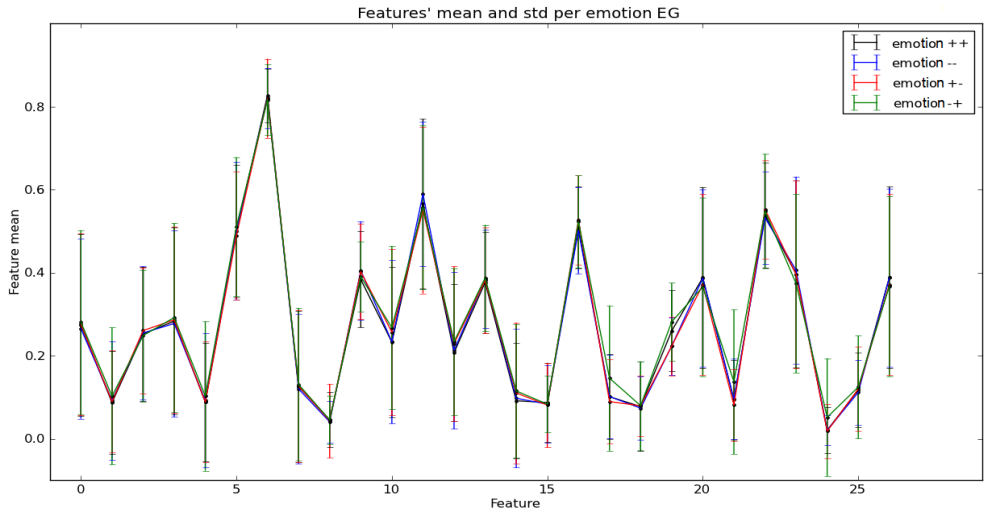


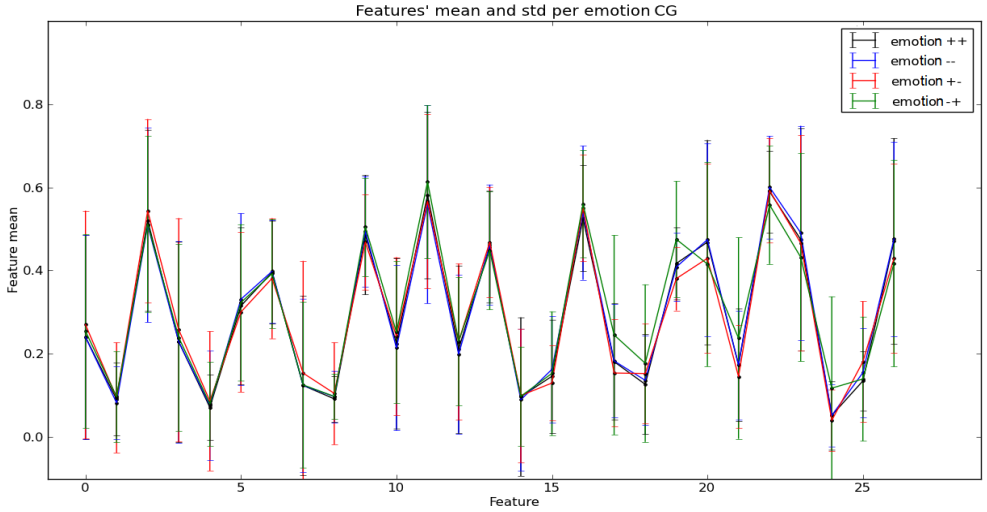
Figure 36. Feature distribution in PCA space

In Figure 37 the mean and standard deviation of the features per emotion are plotted for the two different groups. One can see that there is no evident separation in the mean values of each emotion's features. Plus, the standard deviation intervals are always overlapped, suggesting, once again, similar feature values for different emotions. However, by overlapping of the two graphics pictured in figure 8, it can be noticed that different population groups have different mean feature values which suggest that group separation might be possible. The overlap is plotted in Figure 38. This topic is studied in the next section: population group classification.

Although emotional type classification was not achieved, it is interesting to notice that the features' mean values for each emotion are more distant in the control group case than in the experimental group. Although the evidence is not statistically relevant, this may mean that people with a drug abuse medical record have less distinct physiological responses for each emotion.



(a)



(b)

Figure 37. Features mean and standard deviation per emotion in the (a) EG and (b) CG.

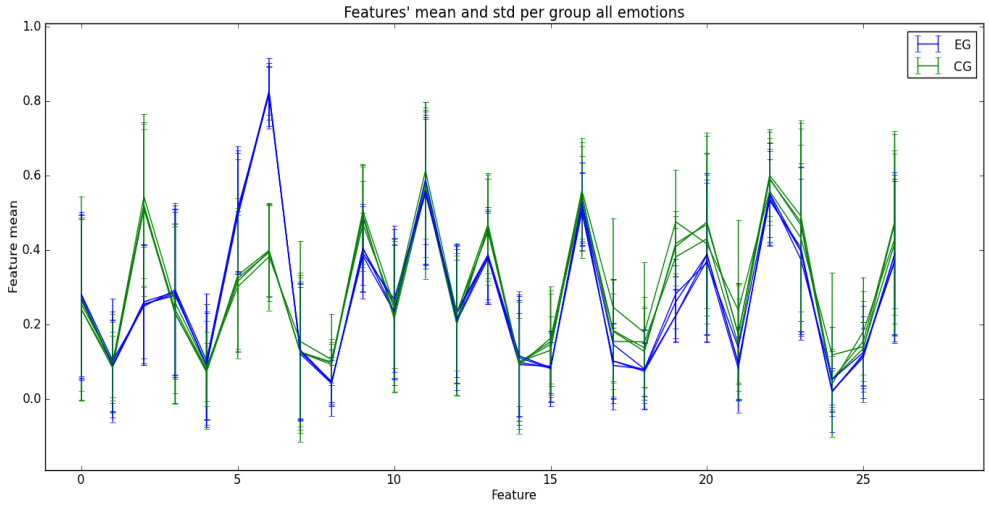


Figure 38. Features mean and standard deviation per emotion in the EG (blue) and CG (green)

4.2.2.2 Population group classification

The following graphics show the mean and standard deviation of the features values per group for each emotion. Most of the features' mean value shows a noticeable separation. For some cases, like the EDA's SCL variance in the emotion ++ and the BVP's skew in emotion +-, there is no overlap of the standard deviation intervals. This means that in emotions like happiness, the abusers group shows a bigger asymmetry in the BVP shape than the control group, i. e., abusers' BVP shows a bigger change between beginning and end of the signal. In emotions like amusement and interest, the non-abusers' group shows a bigger increase of sweat in palms and therefore, an increase of skins conductivity. Figure 40 and Figure 41 show examples of signals where the values of those features are very different.

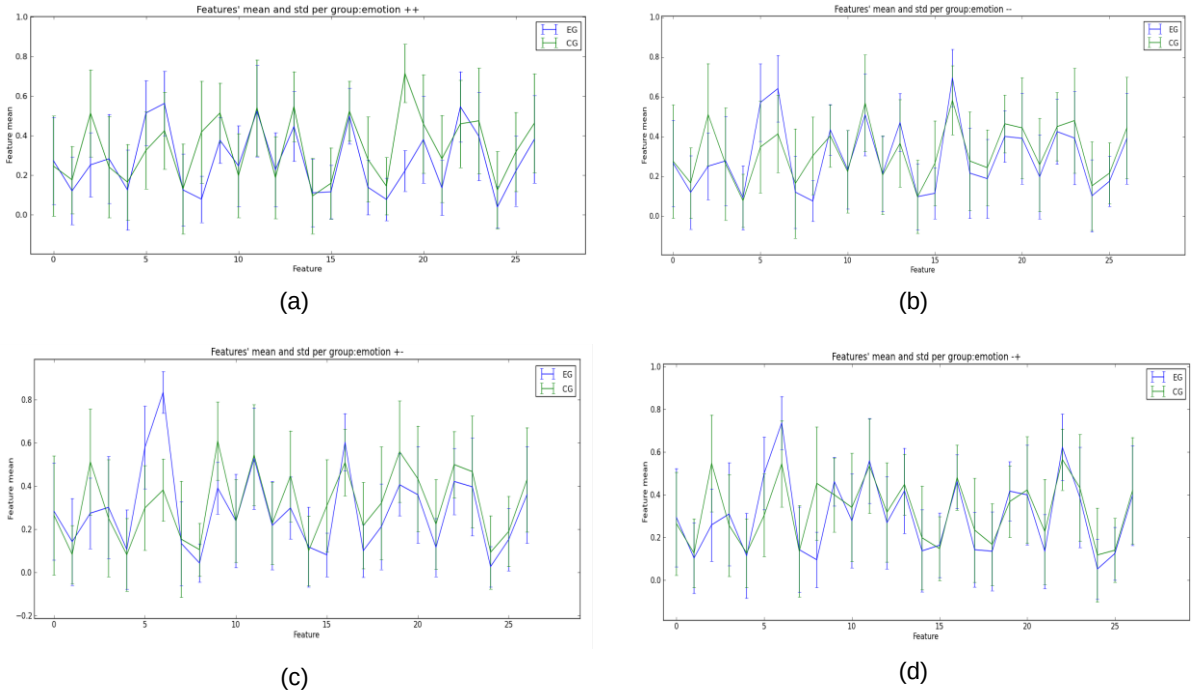
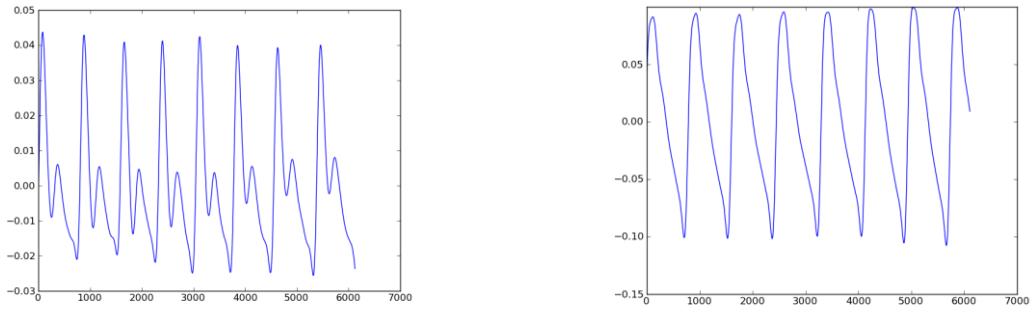


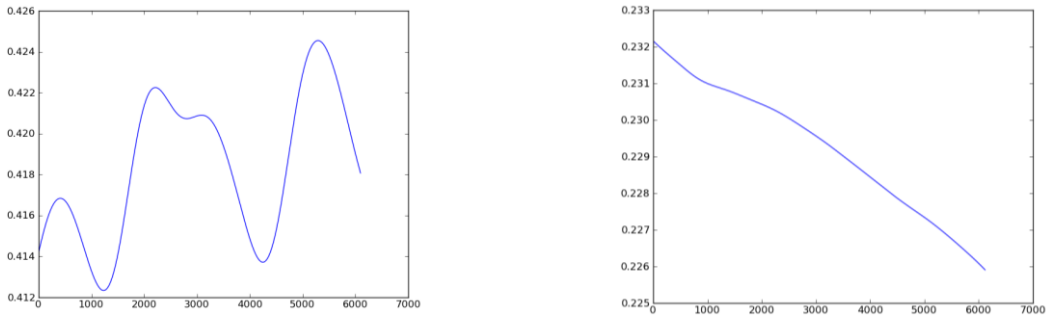
Figure 39. Features mean and standard deviation in the EG (blue) and CG (green), for (a) emotion ++, (b) emotion --, (c) emotion +- and (d) emotion -+,



(a) high skew value (absolute value)

(b) low skew value (absolute value)

Figure 40. Two BVP filtered signals with different values of skew.



(a) positive SCL variance value

(b) negative SCL variance value

Figure 41. Two EDA filtered signals with different values of SCL's variance

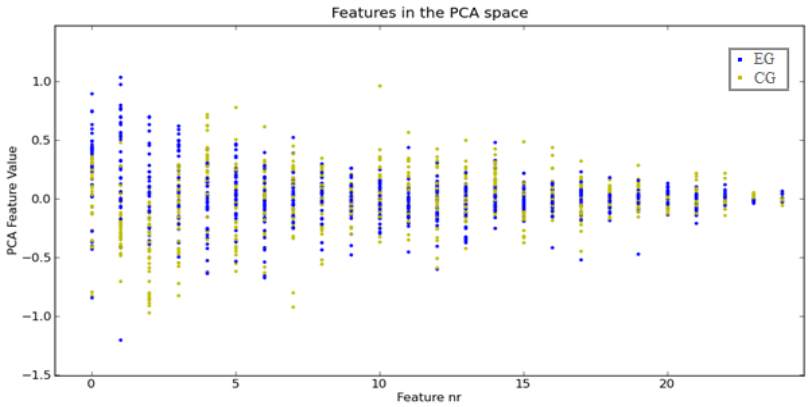
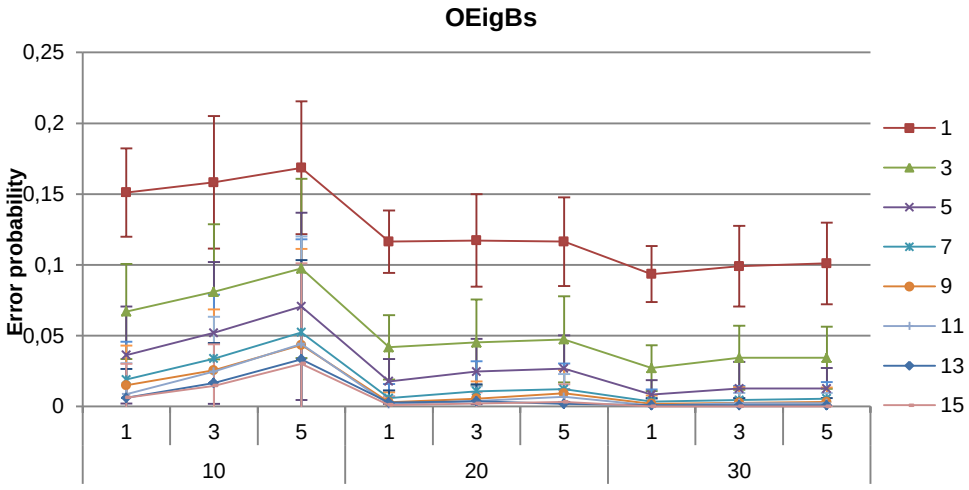


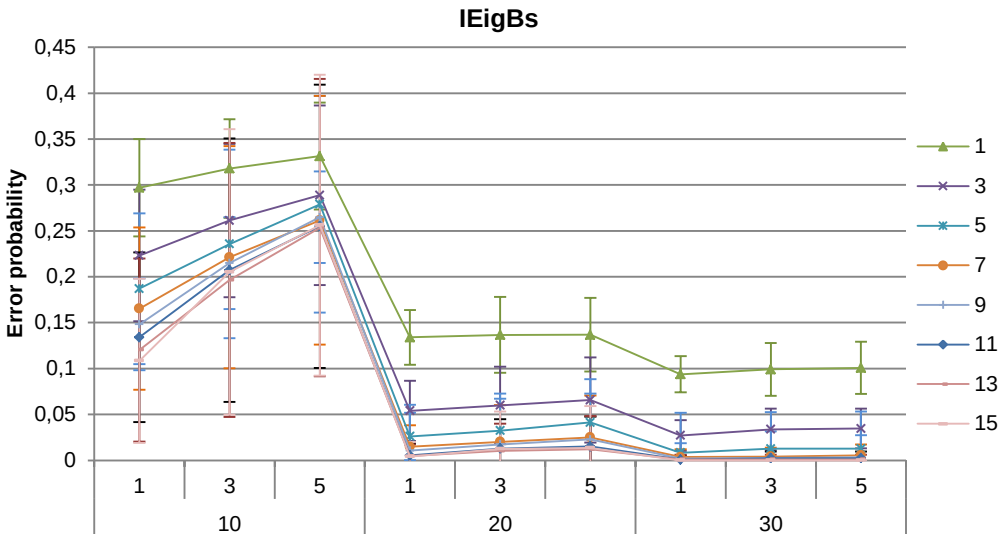
Figure 42. Features' distribution in PCA space for the two groups using all the emotions

The features' values are then converted into the PCA feature space (Figure 42). Also here, some separation is visible.

Several variables are tested such as the number of feature sets for training (*NS*), the number of feature sets need to identify a group, the energy of the eigenvectors kept as templates, the K-Nearest Neighbours used for matching the new data with the templates. The results are shown in the following plots.

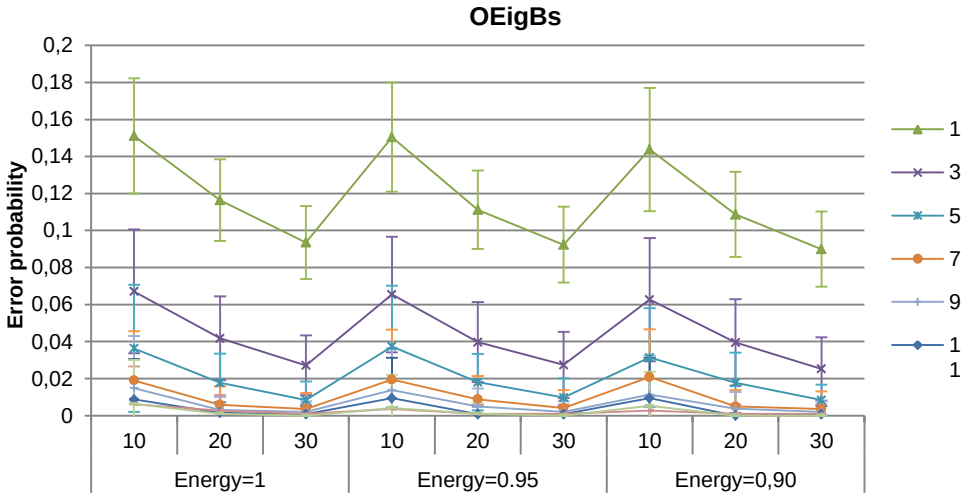


(a)

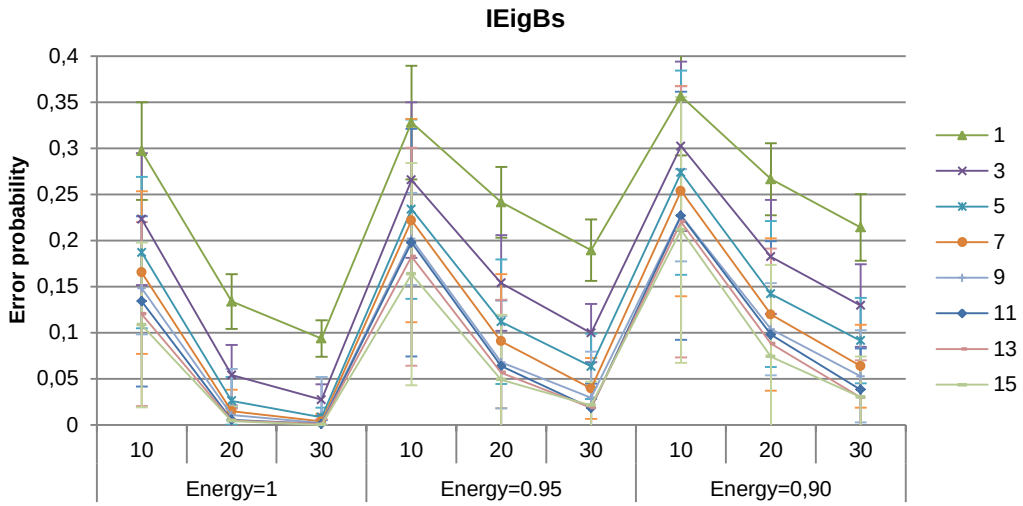


(b)

Figure 43. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method in PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. Energy =1. In the x-axis it is represented the number of segments kept in the data base (NS: 10, 20, 30) and the K-NN value used (K-NN: 1, 3, 5). All the emotions of each group are used.



(a)



(b)

Figure 44. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method in PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. K-NN=1. In the x-axis it is represented the energy values used (energy: 1, 0.95, and 0.90) and the number of segments kept in the data base (NS: 10, 20, and 30). All the emotions of each group are used.

4.2.2.2.1 Number of samples used for data training *(NS)*

The number of samples for training is the number of samples that the system has to know to be able to classify a new sample. In this particular experiment, it can be abstractly related to the number of images watched since each is sample is composed by the concatenated features extracted from the physiological signals acquired during the visualization of one image by one subject.

The values tried for the *NS* parameter were 10, 20 and 30. These will correspond to different percentages of samples used for training according to the test done; these percentages are shown in Table 6.

Table 6. Approximate percentage of data used for training in each classification scenario.

	Number of samples per group	**Absolute number of samples used for training and correspondent percentage**		
		10	**20**	**30**
One emotion	66	15%	33%	45%
All the emotions	264	4%	8%	11%

The higher the *NS* value the better the group's variability will be captured and therefore the lower the error probability will be.

For lower *NS* values the OEigBs method presents lower error values. However, for high *NS* values both methods present similar results since the error in the IEigBs method decreases

dramatically with the increase of *NS*. It is possible to conclude that the Individualized method is less sensible to variations in the *NS* parameter.

4.2.2.2.2 Number of samples used in each test (*k*)

The number of samples used in each test is the number of samples that are given to the system in order to classify a class. In this particular experiment it is related to the number of images that have to be watched by an individual belonging to a class.

Similarly to the *NS* parameter, one can verify a decrease of the error rates with the increase of the number of feature sets given for group identification. However the gain appears to have a lower bound. For *k* values bigger than 7, the error probability doesn't decrease significantly.

4.2.2.2.3 Number of nearest neighbours (k-NN)

The number of k-Nearest Neighbours chosen has little influence in the results when compared with the *NS* and *k*. However, in every case, lower k-NN values lead to lower error rates. This difference becomes less significant for big values of *NS* and *k*.

4.2.2.2.4 Data Energy

The reduction of data energy is associated with a data compression. Table 7 shows the relation between energy reduction and compression.

Table 7. Average compression level of the different *NS* values used for different energies.

Energy \ NS	***10***	***20***	***30***
1,00	0	0	0
0,95	0,52	0,57	0,54
0,90	0,61	0,67	0,65

A small energy reduction (5%) is translated in a data compression of more than 50% in every case. However, from a 5% to a 10% reduction the percentage of compression is not as significant due to the increase of the eigenvalues associated with the eigenvectors that represent the data.

As for the k-NN parameter, energy variations have little influence in the error rates obtained. However, there is a slight tendency for the error to increase with the decrease of the energy. This tendency is more evident for the Individualized method.

When reducing the data's energy, one is removing the eigenvectors that represent lower variance in the data. Usually, the eigenvectors characterize the noise in the data and are thus less significant in the final results. However, the fact that the error values increased slightly indicates that, in this case, those eigenvectors don't stand for only noise, they contain somewhat relevant information. Note that with data energy reduction it is not possible to obtain a 0% error value.

4.2.2.3 Group separability per emotion

The above graphs are created using samples taken from all the emotions of each individual; the separation made was based on the sample's population group. It is also possible to evaluate the groups' separability for specific emotions. That study is presented in Figure 45.

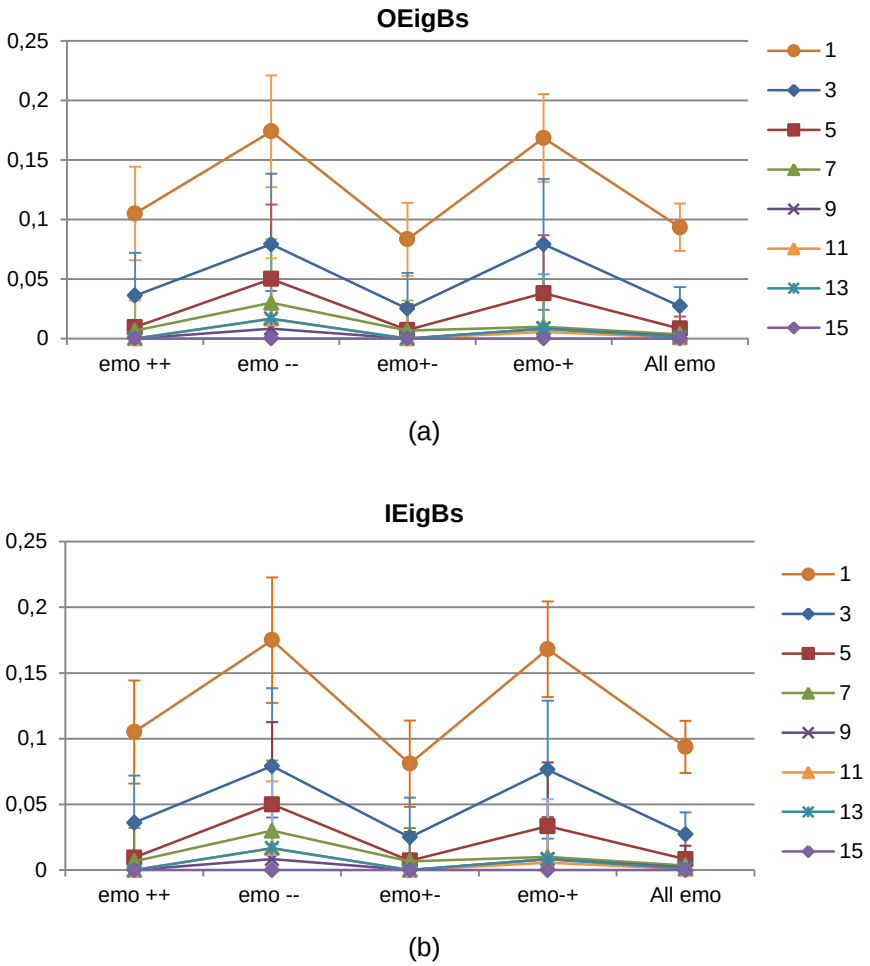


Figure 45. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method for each *k* value used. K-NN=1, energy=1, NS=30. In the x-axis it is represented the 4 emotions used for group separation and all the emotions.

The results obtained with the two methods, individualized population and overall population, are very similar, although not the same. This happens because the *NS* value used was the highest one, 30. As explained before, higher values of *NS* allow a more accurate classification and therefore, closer to the true error value. Thus, similar error values are obtained for both methods.

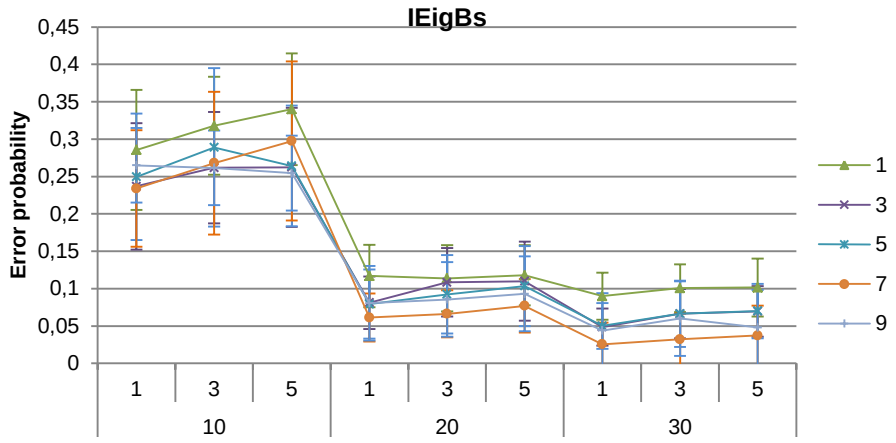
From the graphic shown above, one can conclude that emotions with positive valence differentiate the two groups more effectively than emotions with negative valence. Regarding arousal, the best results are obtained when it is negative. The lowest error values are thus obtained with the +- emotion. These results could be expected after analyzing the graphs in Figure 39, where a bigger feature mean and SD separation was observed in positive valence and negative emotion.

These results imply that drug abusers have distinct physiological reactions in every emotion when compared with the control group. That difference is more evident in +- emotions (e. g.

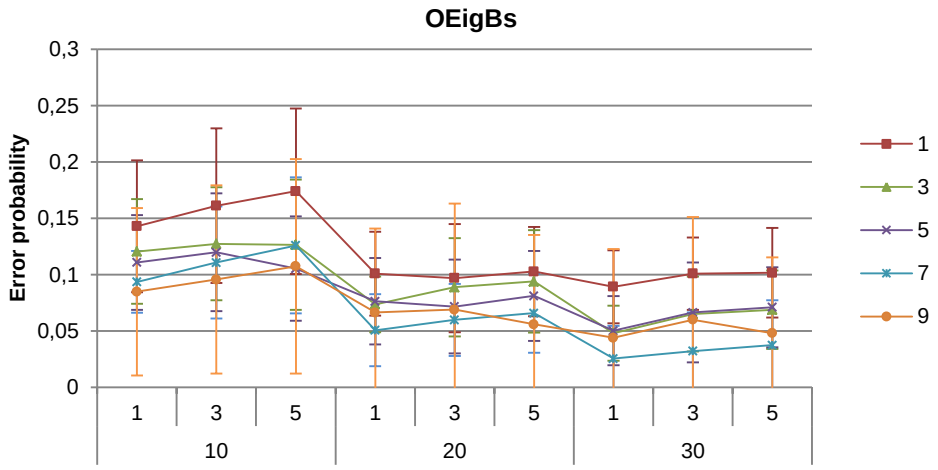
happiness) and less evident in -+ emotions (e. g. anger and anxiety). Using a *k* value big enough, it is possible to distinguish the two groups with a 0% error probability and 0 SD except for the -+ emotion. Emotion -+ was the only case where the error value didn't converge to 0%; the convergence was verified to an error value of 4.56%.

4.2.2.4 Testing with samples belonging to the same individual

In the second approach used, each test was done with samples from the same individual. Only 12 samples per individual are available in the data base. From those 12 samples some could have been chosen for data training. Therefore, a very low number of tests were done with *k*=11 which results in a low statistic relevance of the results. For this reason, and since it has been repeatedly proven before that results of tests with *k* value higher than 9 are very similar, the error values of *k*=11 are not plotted. The remaining results are presented below.

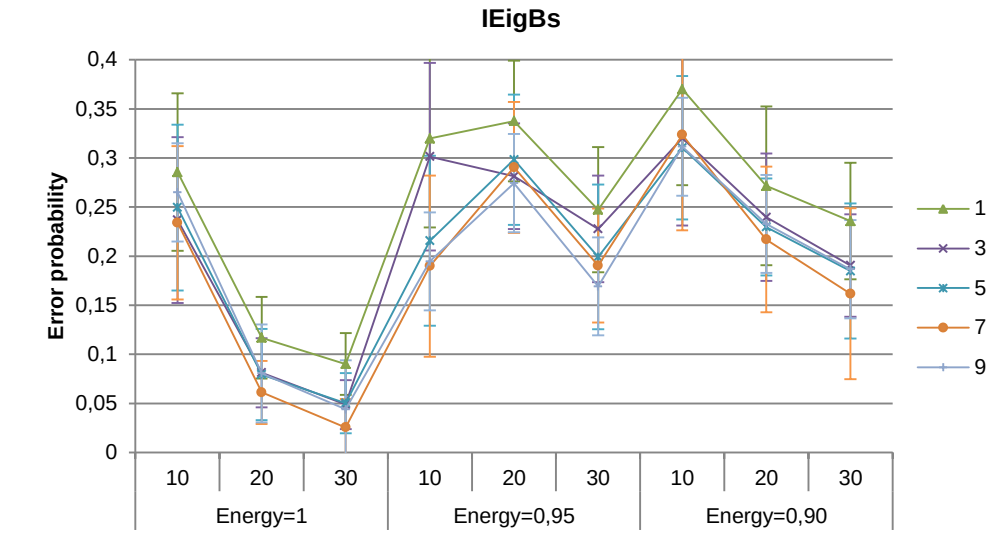


(a)

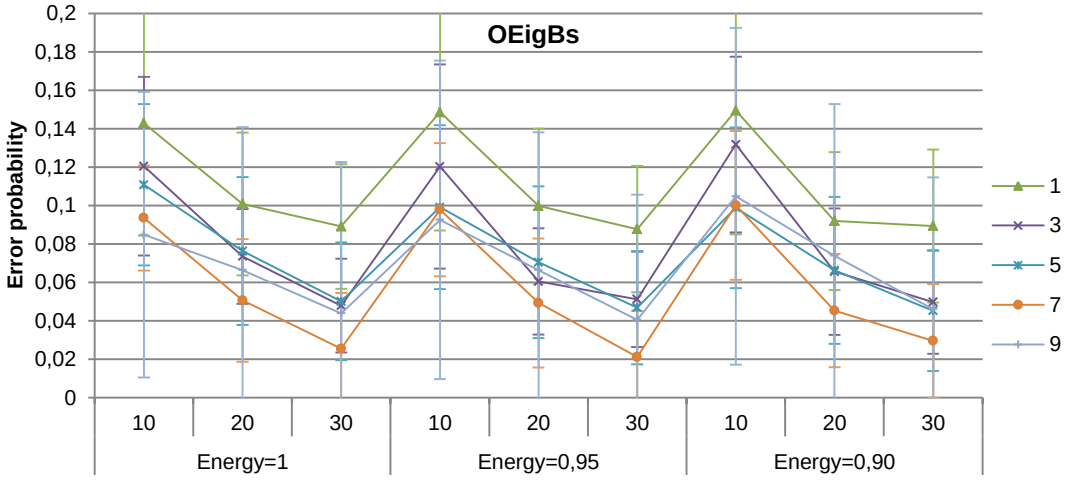


(b)

Figure 46. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method in PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. Energy =1. In the x-axis it is represented the number of segments kept in the data base (NS: 10, 20, 30) and the K-NN value used (K-NN: 1, 3, 5). All the emotions of each group are used.



(a)



(b)

Figure 47. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method in PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. K-NN=1. In the x-axis it is represented the energy values used (energy: 1, 0.95, and 0.90) and the number of segments kept in the data base (NS: 10, 20, and 30). All the emotions of each group are used.

The same conclusions are reached in terms of parameter variation. Higher *NS* values, higher *k* values and lower *k-NN* values allow lower error rates. Regarding the data energy, the IEigBs method revealed once again to be the most prone to error coming from data compression while OEigBs is almost invariant to energy variations.

Comparing this method with the one previously used, where it was assumed that individuals of the same group would have the same physiological characteristics, one can notice that this method has, in general, higher error rates, in specific, 0% error is never achieved. Still, very acceptable error rates are obtained; the lowest errors hover the 2.5%. If one keeps in mind that this recognition system

would be mostly used in decision support (e. g., decision support in the diagnosis of drug abuse), a 2.5% error is a very good result.

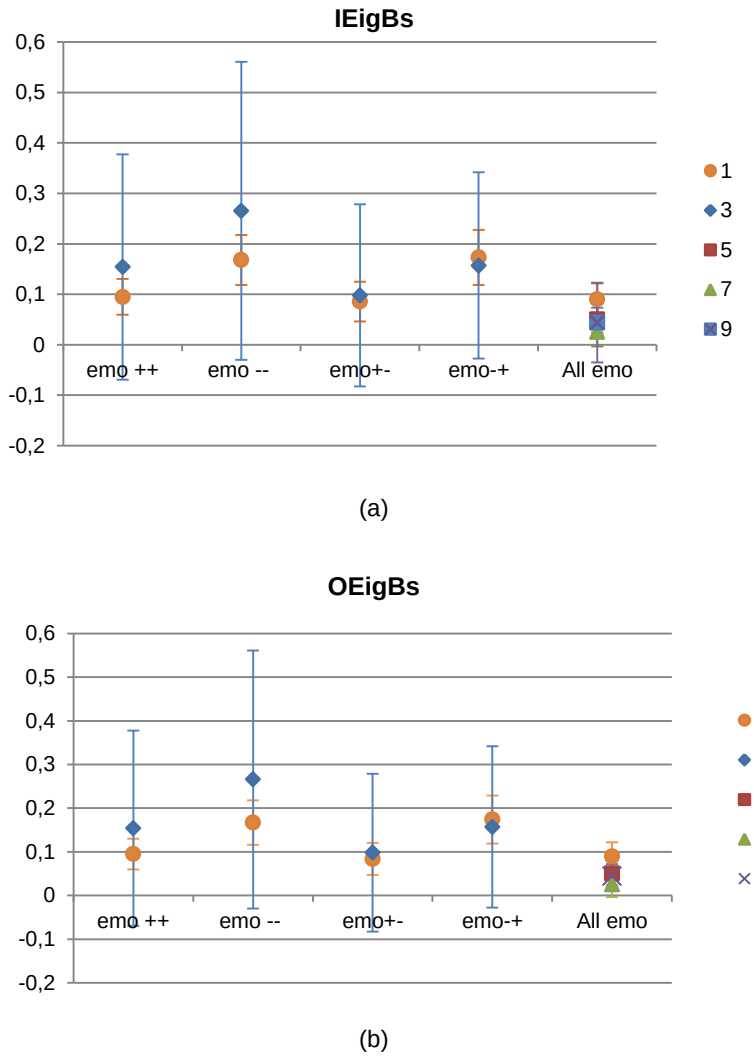


Figure 48. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) Overall Population Method and (b) Individualized Population Method for each *k* value used. K-NN=1, energy=1, NS=30. In the x-axis it is represented the 4 emotions used for group separation and all the emotions

Regarding group separability per emotion, the same tendencies as before are visible, i. e., lower errors in emotions with positive valence. Notice that each individual had only 3 samples for each emotion, so the maximum *k* value possible is 3. Similarly to what happen to the tests using all the emotions' samples, from those 3 samples some could have been chosen for data training. Therefore, a very low number of tests were done with *k*=3 which results in a low statistic relevance of the results.

4.2.3 FIDUCIAL METHOD WITHOUT PCA FOR CLASSIFICATION

As explained before, classification was also tried without the conversion to the PCA space. As expected after inspection of Figure 38 and Figure 39, emotion separation was not possible and

population group separation was. The following figures show the results obtained in population group separation.

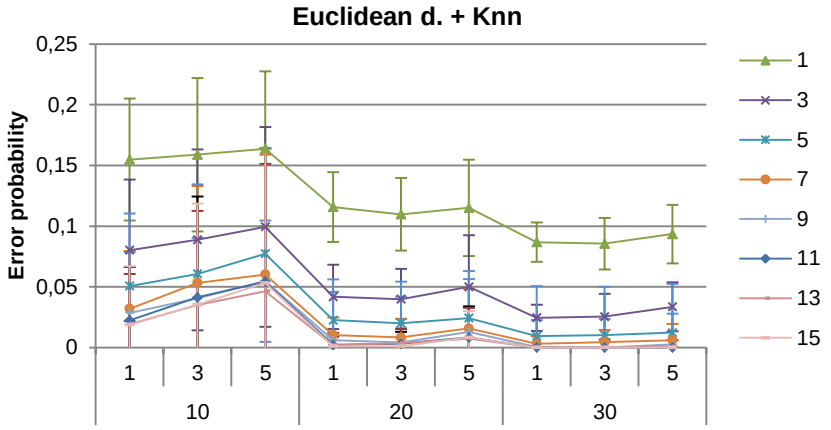


Figure 49. Error probability mean and standard deviation obtained when trying to identify the two groups with no feature conversion to PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. Energy =1. In the x-axis it is represented the number of segments kept in the data base (NS: 10, 20, 30) and the K-NN value used (K-NN: 1, 3, 5). All the emotion of each group are used.

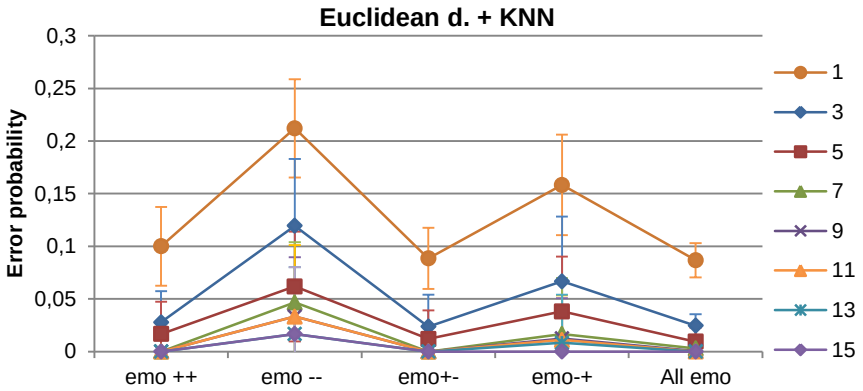


Figure 50. Error probability mean and standard deviation obtained when trying to identify the two groups with no feature conversion to PCA space. K-NN=1, energy=1, NS=30. In the x-axis it is represented the 4 emotions used for group separation and all the emotions.

Results obtained are very similar to the ones of OEigBs. However, for low values of *NS* and *k*, mean values and standard deviation are consistently lower for the OEigBs method. The most noticeable difference is for the -- emotion where both the OEigBs and IEigBs lead generally to lower error values and even allow 0% error classification. Overall, the use of PCA allows better results in situations where separation is more difficult or less evident, e. g., low number of samples in train or test sets.

4.2.3.1 Testing with samples belonging to the same individual

Using only samples from the same individual for testing, the classifier without PCA was also tried.

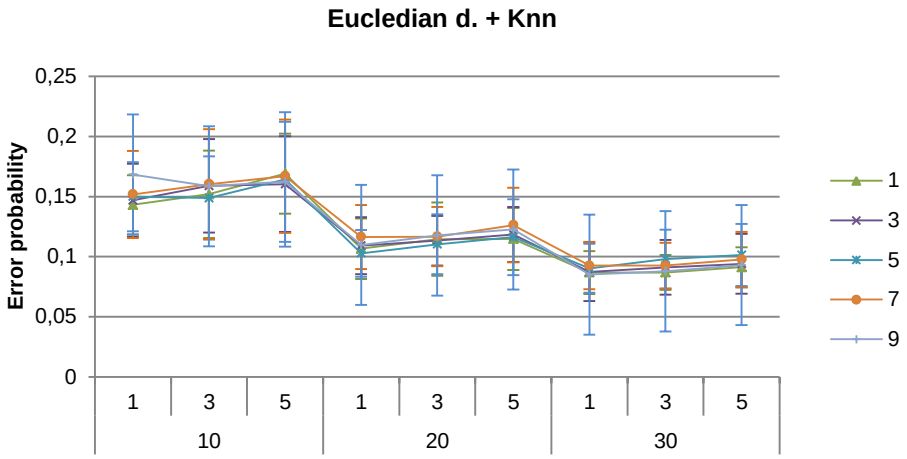


Figure 51. Error probability mean and standard deviation obtained when trying to identify the two groups with no feature conversion to PCA space. Each colour line (numbered from 1 to 15) represents a *k* value used. Energy =1. In the x-axis it is represented the number of segments kept in the data base (NS: 10, 20, 30) and the K-NN value used (K-NN: 1, 3, 5). All the emotion of each group are used

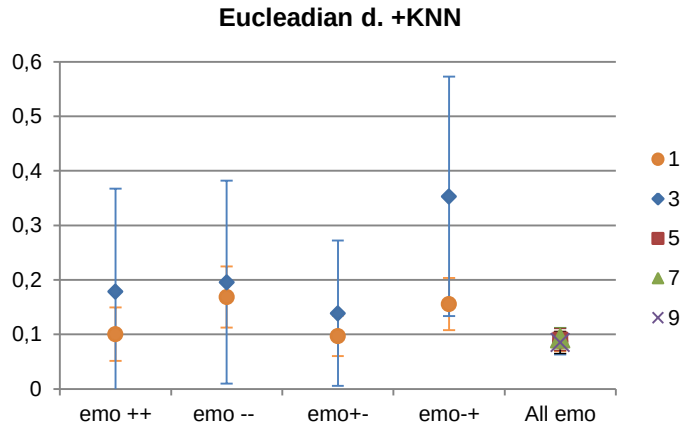


Figure 52. Error probability mean and standard deviation obtained when trying to identify the two groups with no feature conversion to PCA space. K-NN=1, energy=1, NS=30. In the x-axis it is represented the 4 emotions used for group separation and all the emotions.

All the relations between parameters variation and error rates stated previously are verified, consistently proving the truth value of the claims made.

Comparing these new results with the ones obtained before, one can notice that this method leads to the highest error values obtained so far. The lowest errors obtained hover the 8%. This method seems to be the less sensible to *k* value variation. The error mean value is kept practically constant with the variation of *k*, however the standard deviation increases with the increase of *k*.

CHAPTER 5

CONCLUSIONS AND FUTURE DIRECTION

In this work a framework and methodology for biometry and psychophysiological assessment using physiological signals was developed. Several evaluations were done: (a) ECG signal for user identification and authentication; (b) emotion identification; (c) classification of drug abuser patients and non-abuses. The methodology used PCA and K-NN classification and involved several signal specific pre-processing steps such as filtering or feature extraction. Two main classification approaches were proposed, either using eigen representations of a signal or set of features that model the overall population, or using individualized eigen representations per user. The method presents several configuration parameter options that were thoroughly studied in each case.

In situation (a), overall good results were obtained. Using 30 heartbeat segments as templates, and 10 segments for accessing the system, both classification approaches allow obtaining a 0% identification error. Overall Population EigenBs method has presented, in general, the lowest error values, both in identification and authentication. Identification methods allowed an error as low as 0% while for authentication 0.3% was the lowest equal error rate obtained. Results also indicated that authentication method is less prone to errors coming from variation of the classifier's parameters. Template destabilization may occur through time and emotional variation lowering the accuracies obtained. This topic has not been thoroughly studied in the context of biometry; however some works are already trying to compensate this instability. (Agrafioti 2011)

For some parameters' combination, the Individualized Eigen-Bs approach showed similar error values to the ones obtained with OEigBs. Thus, IEigBs is a good solution for the large-scale identification problem pointed by (Agrafioti 2011), i. e., the fact that algorithm training is not done with a proper initial dataset. With this method it is possible to "train" the algorithm in each enrolment with a low computational effort.

The down side of ECG-based biometric methods is that the enrolment time and accessing the system time increases for better accuracies (around 30 seconds of enrolment and 10 seconds of access time for a 0% identification error rate). However, this biometric modality is less prone to forging than more conventional modalities, such as the fingerprint, and can verify the liveliness and stress level of a person, which can be useful to prevent unwillingly identification. This modality is thus suitable for high security systems that require liveness and will prove discarding the time required for recognition. Ongoing work includes a further enlargement of the population set, and extending this study to situations of multiple acquisitions at distinct time instants.

In psychophysiological assessment (emotions and population distinction), IEigBs and OEigBs were used for identification of psychological states after feature extraction in physiological signals. For comparison proposes, a method without PCA was also applied. In it, after feature extraction classification was done using only a Euclidean distance based K-Nearest Neighbours classifier.

Situation (b) wasn't successful. Neither of the methods tried allowed distinguishing between emotions. After some investigation, it was concluded that the feature values of different emotions' signal overlapped. Therefore, future work should focus mainly in extraction of new features, analysis of different physiological signals or development of active arousal elicitation method for new acquisitions, which proved to lead to better accuracies in emotion identification (Agrafioti 2011).

Situation (c) showed that it is possible to classify a user as drug abuser or non-abuser with a 0% error value using any of the methods tried (PCA+ K-NN or K-NN). However, although low values of error are achieved using all the samples available, regardless of the emotion, for emotions with negative valence and positive arousal (such as anger), 0% error is never reached. Conversely, the emotions that allow lower error values in every test are the ones with positive valence and arousal (such as amusement and interest). Concerning the most distinguishing features, BVP skewness and EDA SCL variance stand out for emotions -+ and ++, respectively. This method is useful for diagnostic support of drug abuse conditions. Future work should include the enlargement of the database and maybe enlarge this study to individuals with other psychophysiological conditions. Unbalanced datasets, such as the one used in this experiment, can bias the results. To avoid that, random sampling was applied to the experimental group. Other methods can be tried for data balancing, both in sample selection and regarding the algorithm used for classification (such as a Bayesian classifier where an *priori* probabilities can be assigned, or Neighbour-weighted k-NN (S. Tan 2005) where each neighbour is weighted according to its class size).

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