Biometrical and Psychophysiological assessment through biosensors

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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.**

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.

I. INTRODUCTION

Several factors, such as genetic, social and environmental, shape one's physical and psychological characteristics, which mean that among approximately 7 billion human beings, there are no exact copies. Making the distinction between individuals and behaviours has been of extreme importance, e. g, distinguishing between familiar faces and strange ones or distinguishing between other's positive or negative reaction to one's behaviour, etc. Thus, machine recognition is necessary for a human-automate interaction that is more accurate and more similar to human interaction. This work is divided in two daily life recognition tasks: individual's identity recognition and individual's psychological features recognition.

A. Automated human identity recognition

If previously introduced, humans are frequently able to recognize others, based on their visible physical macro characteristics. Nevertheless, when one talks about automated human recognition, other common options come to mind, such as fingerprint recognition or iris scanning. These kind of structures are too complex, and not typically accessed by the human senses, for the average human brain to use it in recognition. 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 physiological/behavioural characteristics which may be used to distinguish and recognize individuals. These characteristics are generally referred to biometric features and will be further explored throughout this work.

B. Automated psychological features recognition

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 and psychological characteristics. Automated psychological features recognition systems are harder to deceive since it is difficult to mask or alter physiological signals. 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 the consumption of harmful substances, may lead to physiological alterations. Some of these physiological changes can only be detected with computational help. Trained recognition systems can detect abnormal physiological patterns and diagnose problems such as Alzheimer or drug addiction.

C. Article structure

This article is divided in 5 sections. The first is an introductory section, where the motivation is explained. The second section presents the background and related work where the main concepts and previous knowledge required is exposed. The third section gives an overview of the methodology used. The forth section is where the results of applying the proposed methodology to real physiological signals are presented and discussed. The fifth section concludes this article and presents ideas for future work.

II. Background and Related Work

A. Pattern recognition and classification

Although it seems simple, pattern recognition is actually a very complex process. Machines have the potential to discover patterns undetectable by the human senses. For that reason and for automation purposes, it is of great interest to design and build machines that can recognize patterns. The design of a pattern recognition and classification system consists of some standard steps: data collection, feature extraction, model choice, training and evaluation (testing) [1].

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. Information about several classifiers can be found in [1]. In this work Principal Components Analysis (PCA) and K–Nearest Neighbor (KNN) are used as feature extraction / data dimensionality reduction methods and classification methods, respectively, and are thus further described in the following sections.

1) Principal Components Analysis (PCA)

PCA is a statistical method used for dimensionality reduction and data compression. Let $X = \{ X_1 , \dots , X_n\}$ denote a set of signals, each one, X_i, corresponding to a time series (in our case, a sequence of samples composing a heartbeat). 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. Find eigenvalues (λ_i) and eigenvectors (V_i) of the covariance matrix *C*.

e. Sort 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 eigenvalues, $X_i = \sum c_i V_i$, 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 and the higher the energy. Low energy eigenvectors can be eliminated without significant impact in the total data shape.

B. Biometric Recognition

Biometric recognition relies on physical or behaviour traits of subjects to identify them. User identification/authentication systems based on biometrics comprise two main phases [2]: enrolment and identification/authentication (Figure 1). At the enrolment phase, the user provides both his/her identity 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.

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. In authentication, the individual intends to be recognized according to a claimed identity (that should be given to the system). The system will compare the authentication data, with the templates available for the claimed user identity (template matching 1:1). 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.

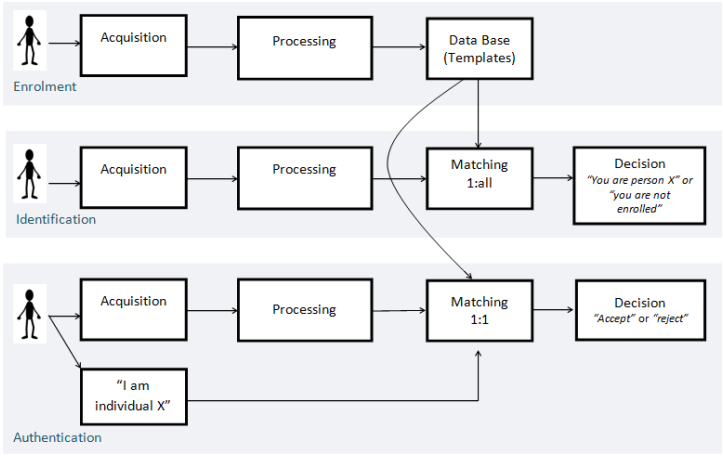


Figure 1. Enrolment, identification and authentication process

1) Electrocardiogram as a biometric measure

The trait used as biometrics in this work is the ECG (recording of the variation of the potential generated by the heart's electrical activity). However, there are no exact copies; there is anatomical/physiological diversity in different individual's hearts, and therefore ECG signal differentiation between individuals is to be expected. Through pattern recognition techniques, this variability can be detected, allowing the recognition of different individuals.

The EGC signal surpasses some of the limitations of common biometrics methods; its intrinsic aliveness detection, makes it difficult to deceive or imitate from latent or unauthorized reproduction of the patterns, contrary to the fingerprint or the voice/face recognition methods. It is practically spoof prove since one cannot modulate or disguise one's ECG signal. Also, it is correlated with the emotional state, making it possible to detect if the person is being forced to do it. 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 [3]. 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 or 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 f*ailure to enrol* (FTE) rate. Most of the existing ECG-based biometric identification systems rely on a fiducial approach [4–7]. However, non-fiducial methods are also referenced in the literature [8], [9]. 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 [10], [11]. For simplicity, these will also be denoted as non-fiducial methods. A summary of these studies is presented in Table 1. This work is closely related with the works by Irvine et al. [12] and Israel et al. [13], where PCA is applied. However, while in previous works an eigen-heartbeat is computed from the overall population, this work proposes individualized eigen-heartbeats computations, which characterize each individual.

TABLE 1. SUMMARY OF PREVIOUS STUDIES.

Reference	Feature	Method	Subjects	Accur.
[4]	Fiducial	PCA	20	100%
[5]	Fiducial	Template Matching + DBNN	20	100%
[6]	Fiducial	FSE	26	99.97%
[7]	Fiducial	LDA	29	98%
[8]	Non-fiducial	Wavelet Distance	35	100%
[11]	Non-fiducial	Cross Parsing + MDL	19	100%
[9]	Non-fiducial	Wavelet Distance	50	95%
Proposed	Non-Fiducial	PCA + K-NN	65	100%

C. *Psychophysiology*

Psychophysiology is a brunch of psychology that describes the mechanisms that link psychological processes. This relation's study involves pattern finding in physiological signals acquired in certain psychological and psychosomatic conditions. [14] Alterations in psychophysiological features are mediated by the peripheral nervous system and can be measured and quantified using biosensors. In this work three biosignals are used for psychophysiological assessment: BVP, RESP and EDA. Emotional pattern finding in humans with and without a drug abuse clinical record, and drug abusers' vs. control psychophysiological profile, will be studied. With that in mind, emotions theory and psychophysiological effects of drug abuse are addressed in the next subsections.

1) *Emotions Recognition*

Similarly to what happens in human interaction, it can be very interesting to have machines that can interpret human emotion. Recently, science has recognized the importance and potential applications of automated recognition of emotional patterns. That field of studies is part of a larger branch called affective computing.

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 [15].

2) *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 [16]. Understanding these physiological alterations can help in diagnosis and treatment of addiction and weakening or eliminating addictive habits and cravings. In this work, physiological signals are used to characterize a drug abuse and a control population.

III. METHODOLOGY

The general classification method used follows the steps in Figure 2.

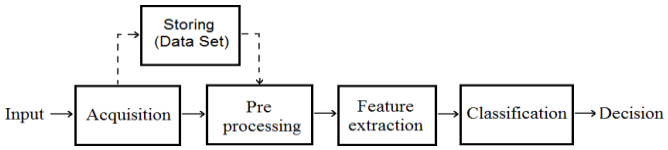


Figure 2. Scheme of the pattern recognition system developed in this work

Due to the different steps required for pre-processing and feature extraction for the two data types analysed, the methodology is divided in: *Biometrical data and Psychophysiological data.*

A. *Biometrical data*

A three step pre-processing procedure is proposed, as detailed next: filtering, segmentation and outlier removal.

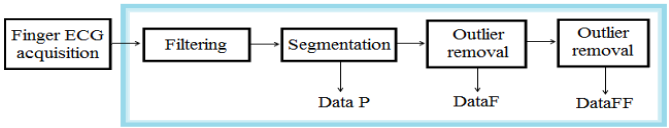


Figure 3. ECG pre-processing (framed) and context

1) *Filtering*

The ECG signal acquired at the finger level can be affected by several noise sources. 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 some of these artefacts.

2) *Segmentation*

This work builds on the work of Engelse and Zeelenberg [10] for offline QRS detection, and adapted for real-time QRS detection. A detailed description of the algorithm and comparison with offline approaches can be found in [11].

Making use of the R peaks detected, each heartbeat template is defined as the signal within a 0,6 seconds window going from 0,2 seconds before, until 0,4 seconds after the peak. Since the sampling rate is 1000 Hz, one considers each template as a sequence of 600 points (R-peak centered at point 200).

3) Outlier Removal

Due to segmentation errors or remaining noise, after the segmentation step, there was a need to remove outliers from the signal. For that purpose, an outlier removal heuristic based on the median of the signal in selected points was created. Considering the expected stability and reproducibility of PQRS complexes, amplitude statistics around certain fiducial points are computed, considering as outliers segments that present deviations from the median statistics larger than an α parameter. The points chosen were the time instants:

- 75, approximately where the P wave is located;
- 150, just before the Q wave;
- 200, where the segments are centered – R peak;
- 300, just after the end of the repolarization.

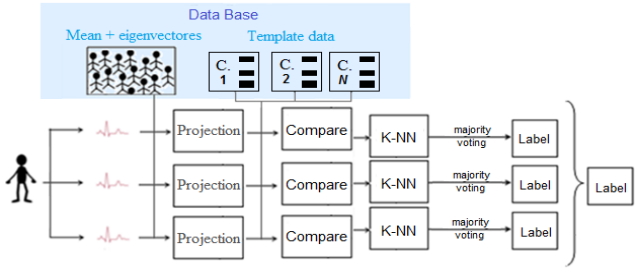
Outlier removal is part of the pre-processing phase for every data acquisition. The outlier removal procedure is applied once or twice in sequence; corresponding remaining (clean) data after the one or two steps approach is hereafter referred as DataF and DataFF, respectively.

4) Template Creation and Decision Process

Four classification perspectives were used. They all built on the same principle: applying PCA to heartbeat data (feature extraction and dimensionality reduction perspective), and using a k-NN classifier for matching new data with template data. The first method, hereafter referred as the Overall Population Eigen-Biosignal (OEigBs) approach, leads to a database formed by the population mean sample and eigenvectors computed from the overall classes' data. Each training set group will be represented by the coefficients resulting from the projection of its samples into the database eigenvectors. 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 training set class those three components will be taken and stored.

a) Identification methods

In the OEigBs 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 4(a)), and the feature vectors thus obtained are matched with the templates of training data. According to the IEigBs 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 4(b)). Template matching uses the Euclidean distance and 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.



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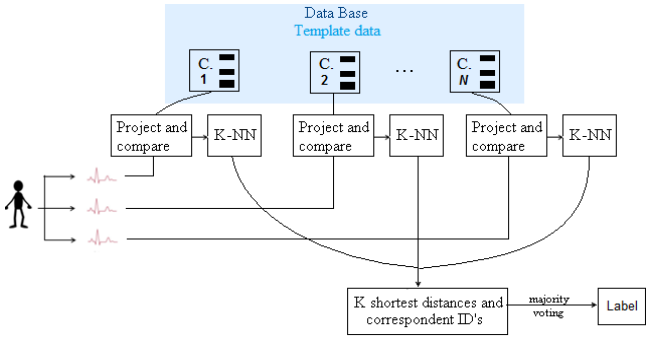


(b)

Figure 4 (a) OEigBs and (b) IEigBs identification scheme. The stickman symbolizes the test input that is being identified. The red signal symbolizes the pre-processed biosignals (including feature extraction) from the individual.

b) Authentication methods

Also here, the two different PCA perspectives were used. In the OEigBs method, the new samples 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 5). In the IEigBs perspective, the new samples will be projected onto the eigenvectors stored under the claimed ID. As a result, each new sample will be represented by coefficients, which will be compared with the ones stored for the claimed ID (Figure 6). The comparison between test samples and templates is done using Euclidean distance. The new sample will be accepted as genuine if the Euclidean distance measured is under a certain threshold. When comparison is done using more than one sample, the decision is done using a majority voting scheme.

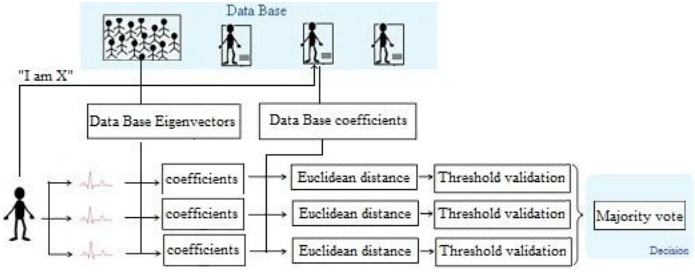


Figure 5. OEigBs authentication scheme.

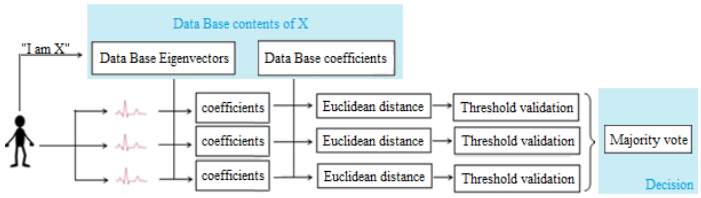


Figure 6. IEigBs authentication scheme.

B. *Psychophysiological data*

The overall system for psychophysiological data analysis comprises a pipeline of modules, summarized in Figure 7.

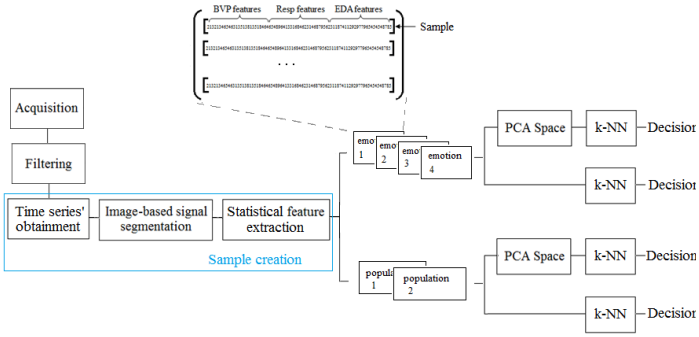


Figure 7. Methodology for psychophysiological data processing and analysis

1) *Filtering*

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 and lower cut-off frequency of 1 and 0.1 Hz, respectively; 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.

2) *Sample Creation*

a) *Time series measures' obtainment*

From the BVP signal, the Heart Rate (HR) and Inter Beat Interval (IBI) were extracted. IBI is measured in seconds and is the time interval between individual heart beats. IBI and HR can be obtained through the formulas:

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

$$HR(x) = \frac{1}{Nb}\sum_{i=1}^{Nb}\frac{60.0}{IBI(i)} \quad (2)$$

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

For the RESP signal, the instantaneous respiratory frequency (RF) was computed. The inverse of the time between alternate zero crossing gives the RF.

EDA has two main components – Skin Conductive Response (SCR; a high frequency component associated with the EDA events) and Skin Conductive Level (SCL; a low frequency component, associated with the EDA's baseline). The method proposed by Gamboa [17] was used for SCR detection. SCL was computed by filtering the signal using a Butterworth filter with an uppercut frequency of 0.05 Hz.

b) *Statistical Features*

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 computing of the features extracted from the filtered signal is only dependent on the absolute values that represent the signal over a period of time. The defined features are:

Mean: $$u(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (3)$$

Variance: $$\sigma^2(x) = \frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^2 \quad (4)$$

Absolute Deviation (AD): $$AD\ (x) = \frac{1}{N}\sum_{i=1}^{N}|x_i - u(x)| \quad (5)$$

Standard Deviation (SD): $$\sigma\ (x) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^2} \quad (6)$$

Skewness: $$Skewness(x) = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^{3}{}^{3/2}}{\frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^2} \quad (7)$$

Kurtosis: $$Kurtosis(x) = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^{4}{}^{2}}{\frac{1}{N}\sum_{i=1}^{N}(x_i - u(x))^2} - 3 \quad (8)$$

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

The statistical treatment of the time series measurements varies with the type of signal. For the BVP signal, HR and IBI mean and SD are calculated as described in (5) and (8), respectively. From the RESP signal, the mean of the RF is taken. In the EDA signal, the amplitude (or mean amplitude) of the detected SCR events is used as feature; if no event is detected the amplitude is set to 0. For the SCL, mean, SD and variance are computed using the (5), (8) and (6), respectively.

3) *Classification*

As shown in Figure 7, samples are grouped by emotion type or by population group, resulting in two different analysis of the data: emotions classification or population group classification. The classification method is similar in both situations. In population group classification, tests are made using the samples corresponding to only one emotion and to all emotions indiscriminately.

4) *Template creation an decision process*

After grouping the samples in classes (see Figure 7), 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. Classification in the method using PCA is performed as described for biometric identification (section III.A.4.a). A number of samples are randomly chosen from each class for training while 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. In the second the samples left for testing are sorted so that each test set is composed by samples from the same individual.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Biometric analysis

1) Dataset

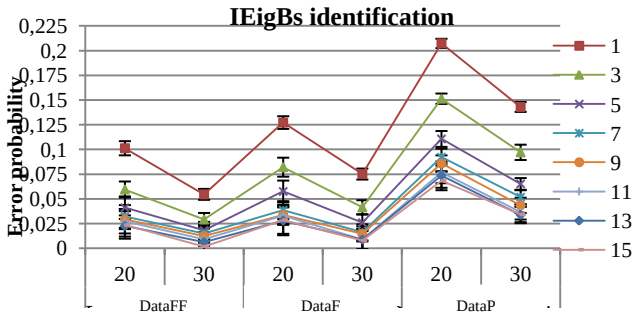
The ECG datasets used in this evaluation were provided by the *Check Your Biosignals Here* initiative [18]. The dataset comprises a one session of acquisition of different physiological signals, including the ECG, in a 65 volunteering individuals' population, in an environmentally unconstrained setup. 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 of a video sequence. The acquisition time was thus variable. ECG signals were collected from fingers and palms using dry Ag/AgCl electrodes.

2) Outlier removal procedure

Due to variable acquisition times, for different individuals the total number of segments (samples) varies. Also, there are different number of outliers for each individual. To standardize the number of samples (*NS*) used as templates per individual, the *NS* kept in the enrolment phase was made constant. *NS* samples are randomly chosen for training, and the remaining segments per individual, after outlier removal, are used to assess the identification accuracy (test data). Error estimates were performed by averaging over 25 runs of the classification procedure. For some individuals and α-values combinations, the minimum *NS* established was not reached. Those were counted as individuals that "failed to enrol". 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, larger identification error rates are obtained. Considering the two identification methods, the lowest identification error rates, with acceptable FTE rates, are obtained by setting α to 0,4.

3) Number of samples for enrolment (NS)

As shown in Figure 8, the higher the *NS* the lower the error probability is, 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 IEigB approaches. Identification methods apparently are more sensitive to the *NS* then authentication methods, where the error value difference between NS=20 and NS=30 is less evident.



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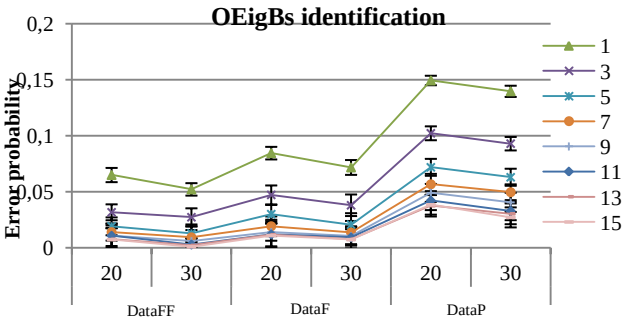

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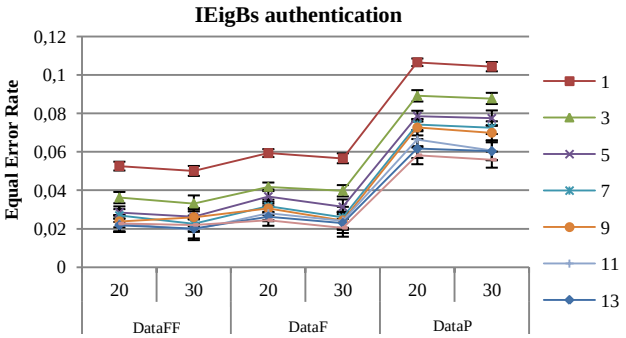

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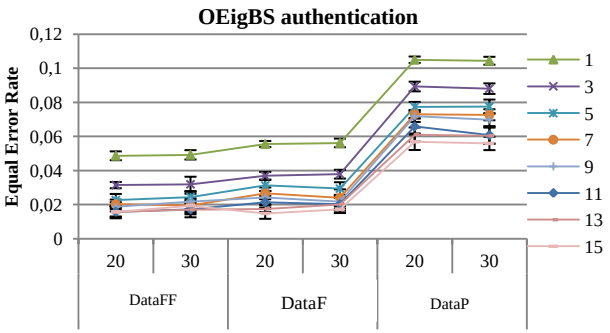


(d)

Figure 8. IEigB identification (1-NN); (b) OEigBs identification (1-NN); (c) IEigBs authentication; (d) OEigBs authentication. Energy=1.Each line represents the number of samples, k, required for accessing the system. In the x-axis the NS parameter and the data used is represented.

4) Number of samples required for entering the system (k)

The number of samples required for entering the system is closely related with the acquisition time in a post-enrolment phase. It is the number of heartbeats that the user provides to the system in order to be identified. From Figure 8, and similarly to the *NS* study, 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.

5) Outlier sensibility

Erro! A origem da referência não foi encontrada. shows an error decrease with the decrease of the number of outliers among the data. Therefore, there is a clear benefit from applying an outlier removal procedure. However, the gain is not so impressive for the second time one applies the procedure. All the methods lead to error probabilities lower than 6% without outlier removal if *NS* and *k* are big enough. However, with DataFF, identification approach can achieve an error probability very close to zero, with a small SD. The authentication approach seems to be less sensible to outliers; it does not reach errors as high as the identification approach for small *k* values and no outlier removal. Also, in authentication, error SD values are consistently smaller

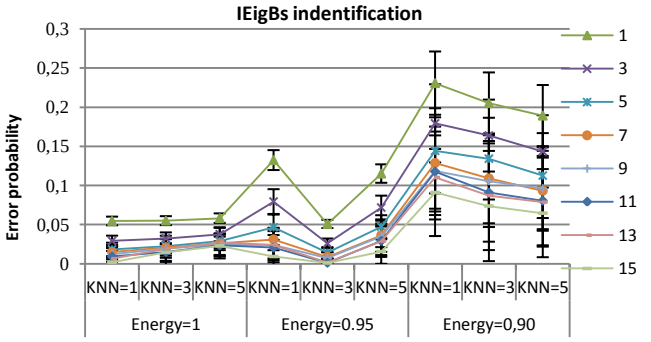
6) Energy

The reduction of the data energy is associated with a compression of the data that is obtained by eliminating some eigenvectors obtained through PCA. 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. In average, a reduction of 5% and 10% in energy resulted in a compression of 50% and 60%, respectively.

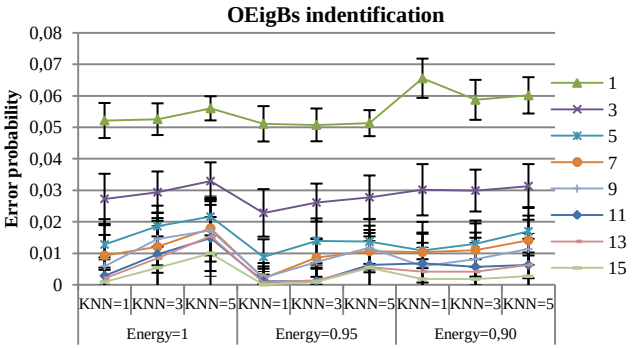
Figure 9 and Figure 10 plot the results for different scenarios with different compression levels. The OEigBs approach is the one that most benefits from data compressing, keeping both the mean and SD similar or smaller with the decrease of the data energy. OEigBs authentication stands out for a considerable 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 IEigBs method, both the mean and SD is similar or increases for lower energy values.

7) K- Nearest Neighbours (K-NN)

As depicted in Figure 9, the number of k-NN 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.

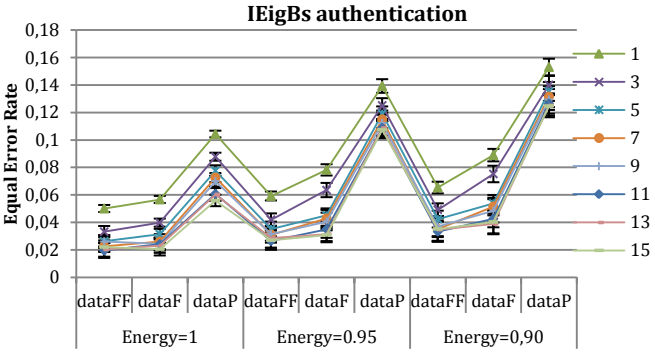


(a)

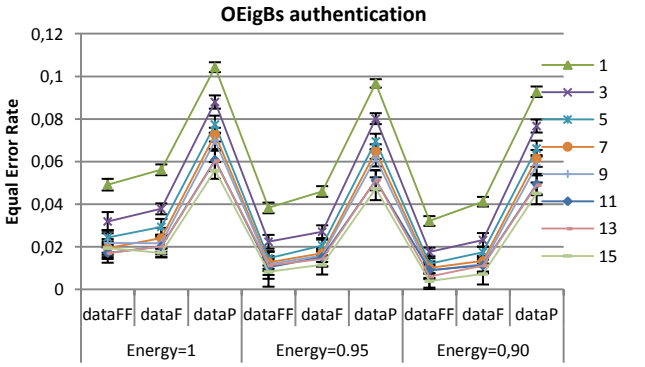


(b)

Figure 9. Error probability variation in IEigBs and OEigBs identification methods, with DataFF and NS=30, for different energy and K-NN values.



(a)



(b)

Figure 10. Error probability variation in (a) IEigHB and (b) OEigBs authentication methods, for the 3 types of data and with NS=30, for different energy values.

B. *Psychophysiological analysis*

1) *Dataset*

Data was collected by researchers from the Faculdade de Medicina de Lisboa, in the scope of a study on psychophysiological behaviour on subjects with a history of drug abuse, when exposed to emotion-eliciting stimuli triggered by a sequence of images taken from the IAPS database [19]. Three physiological signals were collected: Blood Volume Pulse (BVP), Respiratory (RESP) and electrical dermal activity (EDA). Four emotion groups where distinguished based on the valence/arousal values associated with the pictures shown: positive valence and arousal (++), negative valence and arousal (--), positive valence and negative arousal (+-) and negative valence and positive arousal (-+). The database comprises acquisitions taken from 45 patients with a drug abuse record, the experimental group (EG), and 26 control subjects, the control group (CG). Due to errors in the acquisition process, only 41 EG and 22 CG acquisitions are used. In order to have equal size populations, random sampling is applied to the EG. To avoid discarding important information, 30 runs of each classifier test are done.

2) *Classification using PCA for data representation*

a) *Emotion classification*

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

Figure 12 plots the features mean and SD per emotion in both groups. Although there is no evident separation in the mean values of each emotion's features, it can be noticed that different population groups have different mean feature values which suggest that group separation might be possible. This topic is studied in the next section. The features, as they are represented in the features' axis, are schematized in Figure 11.

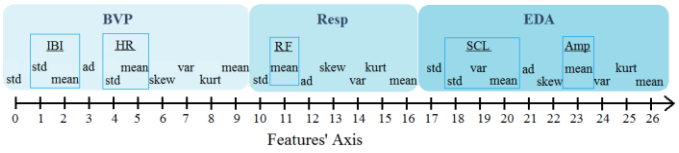


Figure 11 Features' order in the set of features.

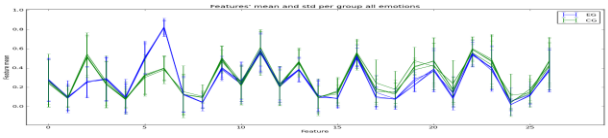


Figure 12. Features mean and standard deviation per emotion in the EG (blue) and CG (green)

b) *Population group classification*

For some cases, like the EDA's SCL variance and the BVP's skewness, there is no overlap of the SD intervals. This means that the EG shows a bigger asymmetry in the BVP shape than the CG. Also, EG shows a bigger increase of sweat in palms and therefore, an increase of skin conductivity.

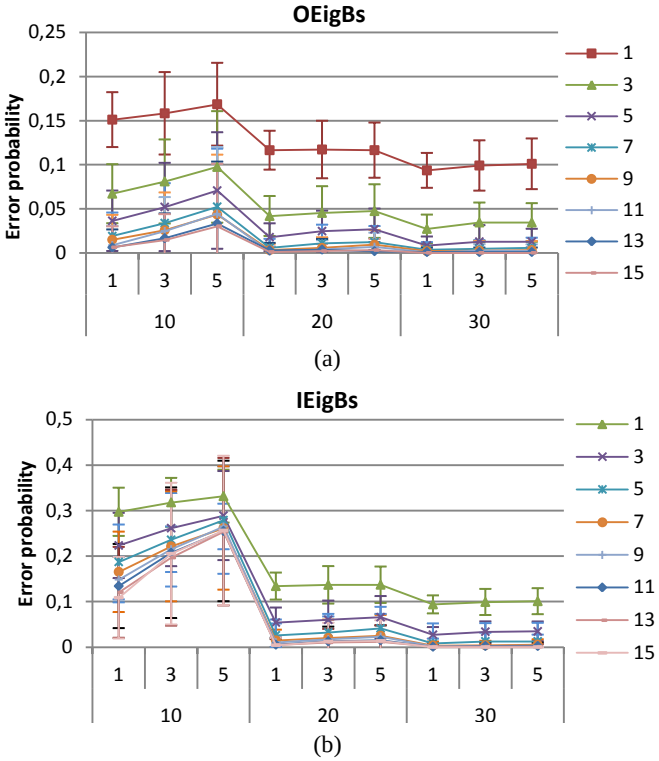


Figure 13. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) OEigBs and (b) IEigBs (PCA space). Each colour line (1 to 15) represents a *k* value used. Energy =1.The x-axis represents the *NS* parameter (10, 20, 30) and the k-NN value used (1, 3, 5). All the emotions of each group are used.

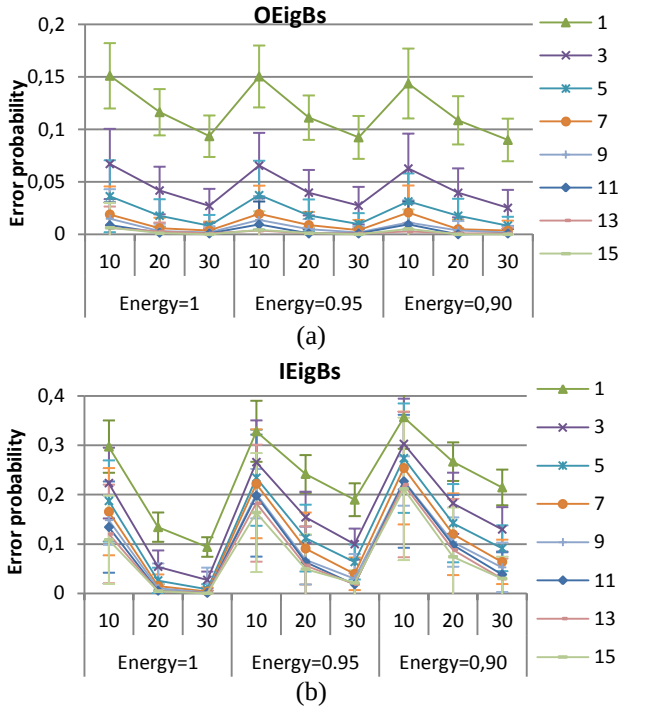


Figure 14. Error probability mean and SD obtained when trying to identify the two groups using the (a) OEigBs and (b) IEigBs (PCA space). Each color line (1 to 15) represents a *k* value used. K-NN=1. The x-axis it represents the energy values used (1, 0.95, and 0.90) and the NS parameter (10, 20, and 30). All the emotions of each group are used.

c) Number of samples used for data training (NS)

In this experiment, the *NS* value can be 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 higher the *NS* value the better the group's variability will be captured and therefore the lower the error will be. For lower *NS* values the OEigBs method presents lower error values. However, for high *NS* values both methods present similar error values. One can thus conclude that the IEigBs is less sensible to variations in the *NS* parameter.

d) Number of samples used in each test (k)

In this experiment it is related to the number of images that have to be watched by an individual belonging to a class. One can verify a decrease of the error rates with the increase of the *k*. However, for *k* values bigger than 7, the error probability doesn't decrease significantly.

e) Number of nearest neighbours (k-NN)

The number of K-NN chosen has little influence in the results when compared with *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*.

f) Data Energy

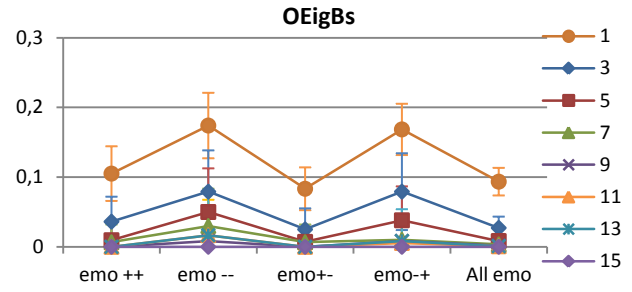
A small energy reduction (5%) is translated in a data compression of more than 50% in every case. Energy variations have little influence in the error rates obtained. However, there is a slight tendency for the error to increase with the decrease of the energy. This tendency is more evident for the IEigBs method. Note that with data energy reduction it is not possible to obtain 0% error value.

g) Group separability per emotion

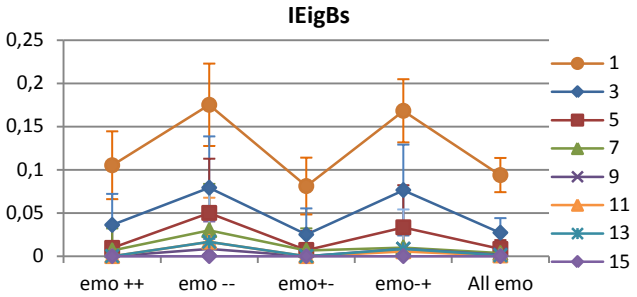
The above graphs are created using samples taken from all the emotions of each individual. It is also possible to evaluate the groups' separability for specific emotions. From Figure 15, one can conclude that emotions with positive valence differentiate the two groups more effectively than emotions with 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 imply that EG individuals have distinct physiological reactions in every emotion when compared with CG individuals. 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%.

a) Testing with samples belonging to the same individual

In the second approach used, each test was done with samples from the same individual. The same conclusions are reached in terms of parameter variation. Regarding the data energy, the IEigBS method revealed once again to be the most prone to error coming from data compression. 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. Still, very acceptable error rates are reached (2.5%). Regarding group separability per emotion, the same tendencies as before are visible.



(a)



(b)

Figure 15. Error probability mean and standard deviation obtained when trying to identify the two groups using the (a) OEigBs and (b) IEigBs 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.

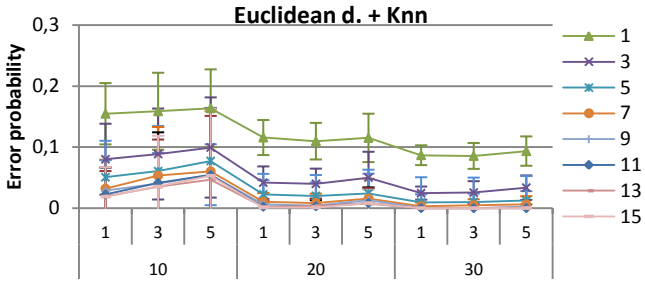


Figure 16. Classification error probability mean and SD of the two groups (without PCA). Each line (1 to 15) represents a *k* value. Energy =1. The x-axis represents the NS parameter (10, 20, 30) and the K-NN value used (1, 3, 5). All the emotion of each group are used.

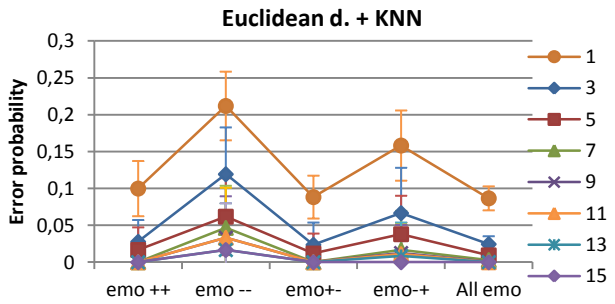


Figure 17. Error probability mean and standard deviation obtained when trying to identify the two groups with no feature conversion to PCA space. K-NN=1, energy=1, NS=30. In the x-axis it is represented the 4 emotions used for group separation and all the emotions.

3) *Fiducial method without PCA for classification*

Also here, only population group separation was possible. Although this method and OEigBs present similar results, for low values of *NS* and *k*, mean values and SD obtained with OEigBs are consistently lower. The most noticeable difference is for the -- emotion where both methods lead generally to lower errors. Overall, the use of PCA allows better results in situations where separation is more difficult or less evident.

a) Testing with samples from the same individual

The relations between parameters variation and error rates stated previously are verified. Nonetheless, this method leads to the highest error values obtained so far (lowest errors hover 8%). Error mean is kept practically constant with the variation of *k*, however, the SD increases with the increase of *k*.

V. CONCLUSIONS AND FUTURE DIRECTION

In this work a framework and methodology for biometry and psychophysiological assessment using physiological signals was developed. The methodology used PCA and K-NN and involved several signal specific pre-processing steps. 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.

In the biometric study using ECG, overall good results were obtained; identification and authentication errors obtained were as low as 0% and 0.3%, respectively. Template destabilization through time and emotional variation may occur, 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 [20]. The down side of ECG-based biometric methods is that the enrolment time and accessing the system time increases for better accuracies. However, this biometric modality is less prone to forging and can verify the liveliness and stress level of a person (useful to prevent unwillingly identification). 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 in physiological signals. A method without PCA was also applied. Emotion recognition wasn't successful and future work should focus in extraction of new features, analysis of other physiological signals or development of active emotion elicitation method for new acquisitions. On the other hand, it is shown possible to classify a user as drug abuser or non-abuser with a 0% error value for any of the methods tried (PCA+ K-NN or K-NN). Concerning the most distinguishing features, BVP skewness and EDA SCL variance stand out. Future work should include the enlargement of the database.

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