Analysis of emotional processes in EEG signals by multidimensional clustering decomposition using wavelet transform

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***Abstract*—This paper presents a signal analysis of electroencephalogram (EEG), focused on characterizing emotional stimulus from audio -visual evocations records. Wavelet analysis was used as features extraction methodology, implementing discrete extraction methodology and analysis of signal characteristics by frequency bands (rhythms) delta, theta, alpha and beta in order to reduce computational burden of the classification space. Joy, anger and sadness, were taken as main references from the Ekman model, representation on the arousal and valence space(AVS) representation, providing this way, spaces of reference with equivalently distributed emotions, which in turn provides a more adequate to interpret and calculate distances between emotions, due that many of the previous models works with well defined emotional states (i.e. with clear ranges where emotion becomes other); This technique allows to implement techniques for calculating statistical metrics on a more simplest way, which in turn provide a framework to allow detection that could serve as a basis for recognition tasks. In general this work generates a methodology of analysis that would provide a way to establish sets of features to be analyzed and the possibility of generating more compact sets for classification tasks in the emotion detection.**

I. Introduction

In the last decade there has been a growing interest in the development of Brain Computer Interfaces (BCI), as part of this the idea of software and hardware manipulation through brain activity has had a major developed [1], and its once the need to analyze the cognitive processes of humans also grows, generating a community-oriented processes linked study the interaction between human and computer. Although the approach is not new, is to this decade when this thematic arises most interest as it has the flexibility of being assisted by many other techniques and methodologies that have been developed further, such as signal processing and patterns recognition; The signal acquisition techniques also have been improved in two of the main techniques for analyzing brain activity (invasive and noninvasive). The use of an appropriate technique for the extraction of signals is essential as will provide the level of analysis and processing necessary for the proper management of data; Within this framework invasive techniques while presenting information with less noise and more accurate information to the source, but it requires a high level of control of either the environment for execution so as well as specialized clinical knowledge, also undergoes physical burden of the study subjects that could interfere with the study because they require intervention or manipulation of the body human, which makes these techniques impractical for most research that seeks to maximize the recognition process without greatly alter the experiment. In the other hand for the non-invasive techniques, many have been already developed, such as magnetic resonance imaging (MRI), electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), magneto-encephalography (MEG), positron emission tomography (PET), among many others. However, the techniques like MEG, PET and fMRI techniques are still demanding technical expertise and are very expensive to implement, which prevents their use in a more generalized way. In this scenario the EEG analysis, is the most feasible to implement mainly because is relatively inexpensive and does not require too much technical skill to use it.

However there is still a lack of standardized benchmarks for comparing any study to be performed, so for this research the DEAP database [2] was used as reference, because is up to our best knowledge the most proper database of physiological signals electrical, it is composed of a set of bio -electric signals stored like: temperature sensors, EEG, EMG, skin resistance and eye movement. This database was built using a technique of audio -visual stimuli and some of the most important aspects to keep in mind is that the signals were stored 32 participants of which 50% are women and the age range is between 19 and 37 years (mean age 26.9 years), check the reference [2], for all the details of this database. As mentioned research of emotion recognition is not really a new issue and has been investigated for several years, however and due to the inherent complexity involved in the definition of emotion, makes the subject matter has been dealt with different approaches and is a current issue with increasing height. This together with the considerations necessary to create ”totally” a methodology to recognize the emotional state of between one person and another, a process that is difficult even for the interpretation of man stipulate a major challenge. However, the development of applications based on the imitation of human responses and interaction with increasingly interactive interfaces, creates a focused development to shorten the threshold between the interaction of humans and machines, as one of the main goals of affective computing. Section 2 shows an overview of the treatment of emotions with a focus on engineering. In Section 3, we address the issue of pre -processing of the signal and as applied in this research. Section 4 addresses the issue of signal processing for feature extraction. Section 5 discusses the methodology that was implemented to develop experiments and finally section 6 addresses the issue of grouping methodology.

II. Emotions

A. Emotions to engineering applications

In the field of psychology, although the topic of emotions results in many different theories and even many philosophical statements, however there are also theories that allow us to interact with them more easily and even from the point of view of engineering, such as the big five model; Particularly our interest is those that allow us to express them in a bi -dimensional space, taking for this as main reference an already well known Aurosal Valence Space (AVS). By combining these models with the theory of Russell and Ekman for emotions, a model based on levels and ranges of emotions is generated, which allow us to characterize an emotional state and generating a well -distributed version for the emotions (anger, joy, sad) as shown in figure 1, mainly referencing to Ekman model of primary emotions [3] [4].

- Valence: Determine or emits the ”trial” to each situation to select between if is positive or negative, including the whole range of possible emotional states between these two extremes (i.e., all possible emotional states to move from a state of lack of interest to excitement or boredom to alertness).
- Arousal: Expresses the degree of an emotion (the level at which an emotion occurs i.e. if this happy or very happy, like spending a joyful state to exited).

While our interest is bi -dimensional space, but there also other dimensions that can be added to this model, such as:

- Domination: Indicates the level of control you have on emotions (i.e. feeling in total control of an emotion or to have no voluntary control. This can also be expressed as a feeling of helplessness and weakness or a feeling of power or being in control).

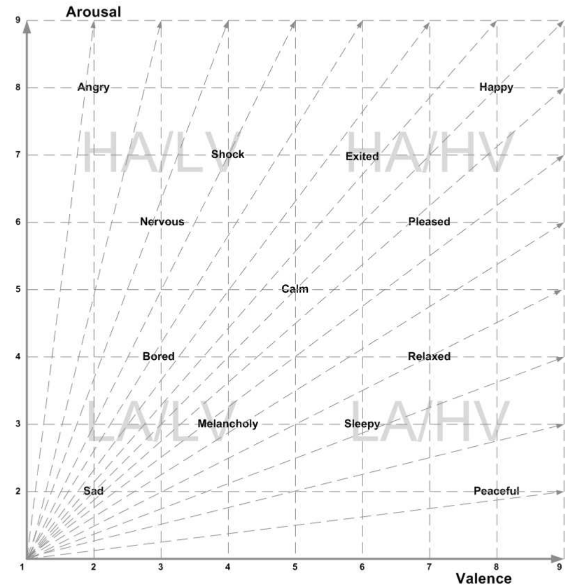

Fig. 1. AVS model with Ekman emotions characterized by non-negative values

- Liking: Specifies the level of pleasure to a stimulus, this allows us to ascertain if the relationship that exists or is proposed between a stimulus and the conscious response of a user matches, helping us create a better correlation between experiment (desired) and response (real).
- Familiarity: Provides a list of user familiarity with the stimuli.

B. Related Work

A notable work was performed in emotion recognition for models based on dimensions in [5], where they developed a model that relates the asymmetry between the right and left frontal lobes of the brain to the emotions. According to Davidson model, emotions are well organized around the front of the brain. The left frontal area is involved in the experiences and emotions interact in an empirical definition of ”positive emotions” and the right frontal region is more related to the experience of what empirically we reference as ”negative emotions”.

As already briefly mentioned, the development of emotion recognition techniques is a very active area in the last decade and therefore have already developed a wide range of related research, perhaps the most popular are based on the recognition and classification of audio signals (human voice) [6] [7] [8], where the main objective of this research is to identify the emotions through the analysis of prosodic features and tone of voice, another popular technique is also the analysis of micro expressions, which is based on the theories of Ekman [3] [9], and the analysis of EEG signals although with different populations like on [10] [11] [12]. One of the most important considerations in the analysis of the research related to the analysis of emotions, is that the emotional behavior may differ between genders as well as between social groups and ages, this impulses the necessity of create the right conditions to induce an emotion in the laboratory frame recreations due that the development of a suitable environment is vital to a successful experiment(currently two main techniques are implemented to achieve this: methods evoked and motor imaginary).

- Evoked or induced: This technique requires a number of stimuli that can be visual, auditory or visual audio, that are related to an emotion, in order to provoke a response and record brain signals to be processed or analyzed.
- Motor imaginary: On this technique the subject is induced to imagine a situation referred to an emotion, but not necessarily; It can also be used in physical limb movement or control situations, another aspect of this model is to refer to an event in from the memory, to remember situations that cause a reaction linked to a specific action or situation; This technique is mostly used in the hardware control like prostheses, using pattern recognition of signals measurements from custom made user profiles.

Being this work subject to DEAP database, it is natural that this research is defined by the emotions caused by audio -visual stimulus (evoked).

III. Signal pre-processing

Due that EEG signals turn out to be highly susceptible to noise, it is important to have a good pre -processing in order to create work spaces which give us less room for error more reliable . The characteristics with which they carried out the extraction of signals is an important aspect, so are described below:

The recordings were acquired by a Biosemi system whose specifications are given in [2], with a sampling rate of 512 Hz , the electrode pattern was 10/20 to 32 channels and 8 additional channels were used to process physiological signals as a auxiliary purpose on the filtering process. As mentioned signals recorded from the scalp, are naturally contaminated with noise and artifacts (eye movement(EOG), muscle movement(EMG), vascular movements(ECG) and kinetic artifacts, the record of these also helps to disposal and reduce the filtering effect; For this purpose a surface Laplacian (SL) was implemented as in [10]. One problem that arises due to the need to pre -process all individuals electrodes signals is the large number of calculations that have to carry out for the analysis, to resolve this the information is re -sampled to 128 Hz and is regrouped by experiments of tri -dimensional matrices; Another important consideration for reducing the complexity of the calculations is to work with the frequency bands in which the human brain operates normally known as rhythms: delta $(0.2\ to\ 3.5Hz)$, theta $(3.5\ to\ 7.5Hz)$, alpha $(7.5\ to\ 13Hz)$, beta $(13\ to\ 28Hz)$ and gamma $(> 28Hz)$, this seeks to establish a limited search area by a band -pass filter from 0.5 to 47 Hz, which is applied to keep only previously identified rhythms of the human brain as a first approximation in this work. The mathematical expression of the filter surface SL is given by:

$$X_{new} = [X(t) - 1/N_E][(\Sigma_{i=1}^{N_E} X_i(t)] \tag{1}$$

where X_{new}: Filtered signal. $X(t)$: Raw signals. N_E : Number of neighbor electrodes.

IV. Signal analysis

For most of the analysis of biological signals, the techniques used are required to provide time and frequency resolution simultaneously, because this kind of problems have as requisite the acknowledgment from the time -frequency at a specific time, as consequence of being biological signals which naturally are not stationary in time; This implies that classical techniques such as Fourier transform (FT) or Fourier Transform Short Time (STFT), are not feasible for its implementation, because although time signals are transformed to the frequency domain, we can only analyze the frequency spectrum of the signal without knowing without an acceptable time resolution. This situation creates a perfect setting for the wavelet transform (WT), which is a transformation that can fulfill the above requirements, because the wavelet transform can analyze the signal in time and frequency scales provides that establish a proportional connection between time and frequency.

A. *Wavelet Analysis*

To analyze the signal wavelet transform is performed for multiple signals, in order to create an average reference function, based on the behavior of all the associated signals. Working only with the reconstruction coefficients of the transformed signal as the wavelet transform relies on a so-called mother wavelet function, Ψ which expands and moves, in order to reconstruct the signal with the waveform defined by a one transformation kernel.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi(\frac{t-b}{a}) \tag{2}$$

At each scale a is a characteristic frequency that can be calculated F_a through the center frequency called mother wavelet, and F_c one sampling period, $Delta\ t$, such that:

$$F_a = \frac{F_c}{a\delta t} \tag{3}$$

The center frequency is the frequency characteristic of the mother wavelet. One way of choosing the parameters of (2), are $a = a_0^m$ and $b = nb_0a_0^m$, where m is called the level. The most common choice of a_0 and b_0 are 2 and 1 respectively. This generates the wave from the transformed signal $x(t)$ as:

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{2^m}}\Psi(2^{-m}t - n)dt \tag{4}$$

V. Methodology

The design of the methodology for analysis and signal processing can be revised in Figure 2, which has been elaborated to agree with following development considerations:

- Gender.
- Right-handed or left-handed.
- Age.
- Nationality.

Data are reordered and analyzed independently by a Daubechies wavelet type 6 (DB6), due to their compact support and orthogonality. Therefore statistical measures are indexed to create three training sets of each emotion, using only the coefficient which has generated a significant percentage of reduction of disk space, ensuring computational cost reduction. Through these considerations, the data can be reordered and

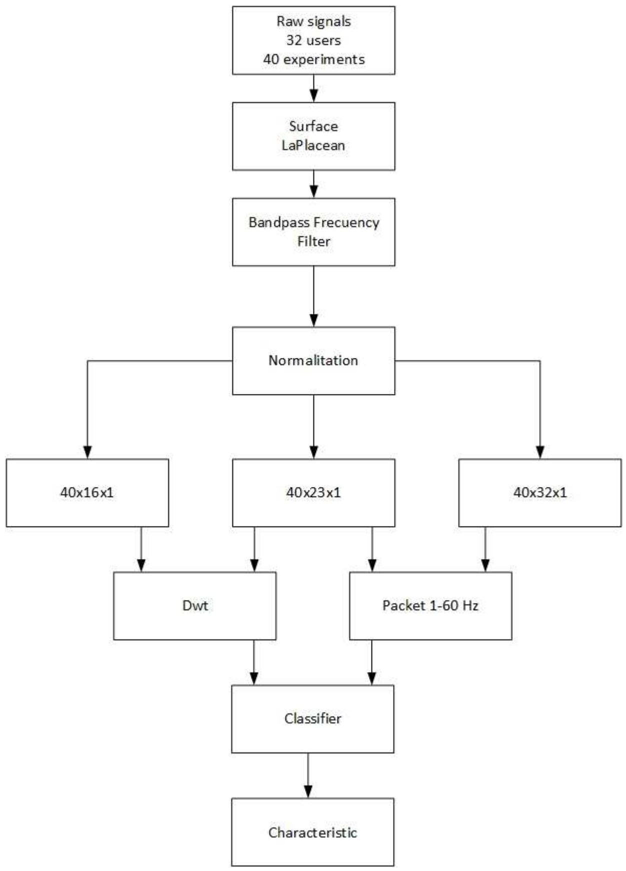

Fig. 2. Signal analysis and feature extraction process

analyzed independently to achieve a dimensional reduction and a level of abstraction that more conveniently is defined by the user. Within the same framework, the implementation of DB6 to provides compact vectors that can be statistical measured and indexed to create three subsets of each emotion employing only the coefficients as characteristic references, this generates a significant data rate reduction and also ensures reduced more computational cost. The contemplation of these considerations also provides some level of independence from the measurements due that this research also assumes clinical differences between genders. However, if one takes into consideration the amount of information to be processed by each of the experiments, rather than generating a reduction, this provides additional dimensions for analysis. In order to solve this problem uses a model very similar to the turbo coding, this meant that will exist various forms of the same information for each type of user (i.e if you are right or left handed, it will generate a vector in a systematic characteristic that will serve as reference for other processing thus eliminating the same processing takes place at each iteration, avoiding the generation of an internal process that runs on each block).

VI. Classification Measurements

To complete the task of evaluating the classification performance, several classifiers that can be used (for example, k-NN, LDA, SVM) [13][14], and because the k -NN algorithm assumes that all instances of the characteristic vectors correspond to points in n-dimensional space, this could represent an efficient methodology, because the determination of the nearest neighbor vectors of the matrix of coefficients as computed from the wavelet transform can be taken, where the vector features would be the average coefficient matrix, which corresponds to an electrode for a single emotion for this to Euclidean geometry can be established by making distances, by two considerations:

- Define the training set used as a reference vector.
- Providing a search function for classifying the vectors (set of representative feature vectors and vector elements depending on the sampling rate).

The choice between the different metrics, is dictated by the computational performance usually associated [14], because of this Euclidean distance was used because it provides an efficient way, through a simple calculation. However also the Mahalanobis distance(MD), may act as a discriminant analysis used as criteria class (sub spaces) and characteristic vector and distance between the centroid of each group; if this were the case, then one MD for each case and each case would be classified as belonging to a single group (which in this case would be a particular emotion, defined by the user), this in order to reduce classification space. The metrics between the eigenvectors, assumes a uniform distribution in the co - variance matrix and are defined as:

$$d_s(\overrightarrow{V_1}\overrightarrow{V_2}) = \sqrt{(V_1 - V_2^T)C^{-1}(V_1 - V_2)} \tag{5}$$

Moreover, the use of k-NN to make a decision on the comparison of a new labeled sample (test data) with reference data (training data), for a given sample space by space x, element closest to the data given the class will be assigned to the class (category) that have the highest number of votes for each case and will be less sensitive to outliers, which is one of the main characteristics of EEG signals the biological signals would be chaotic signals. Another effective method is a linear discriminant analysis (LDA), which provides very rapid assessments unknown input, calculations using the distance between a new sample and the average training data samples of each class, weighted matrices co -variance this LDA trying to find an optimal hyper plane to separate the emotion from other emotions. In addition to the training samples and testing, LDA does not require any external parameter for compaction of the ”discrete emotions”.

VII. Results

The analysis of the coefficients obtained by decomposition with multiple DB6, shows high performance in the reduction of data and a faithful reconstruction of the signal as shown in Figure 3; Grouping these statistics, using a process relating to k-NN, 32 tables and 40 classes, i.e. with k = 32 for each class, achieving this provide a feature space, which define the characteristics, which structures the relationship between emotions in a more compact form as shown in figure 4. These

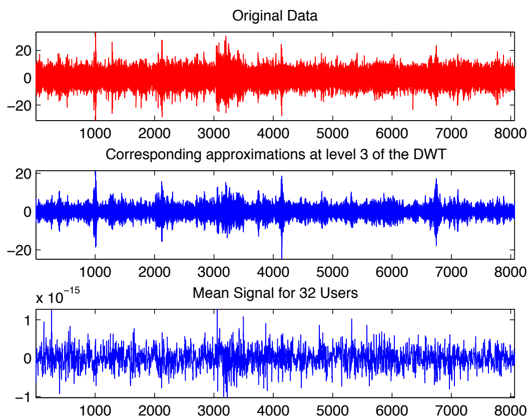

Fig. 3. Reconstructed multi-signal (EEG) analysis with a ”db6” level 3.

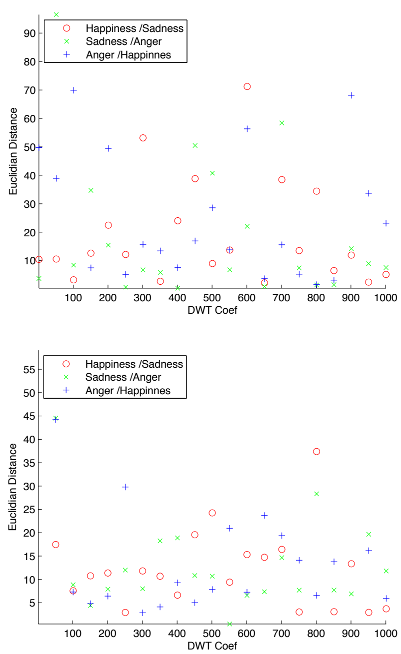

Fig. 4. 1vs1 dispersion of the emotions without and with DWT coefficient analysis.

compact versions provides an alternative solution to generate more adequate spaces of classification, which also could be implemented in clustering techniques, by generating classification spaces and establishing spaces without compromising the computational cost; This process also generates a better dispersion that provides a good insight into the behavior of an emotion in relation to another(characterizing each one as an unique representations by co -variant matrix mean). Another analysis that were performed but this time to observe the in the behavior on the same category of emotions in the AVS, (choosing a single quadrant and the emotions on it and perform the same analysis but to different subject) and the correlation of emotions with different classes (experiments and users), this experiments also shows a dispersion efficient enough for classification and produces a better compacted regions without altering the original data behavior, as shown in figure 5. By employing DB6 transform, we can also find the location

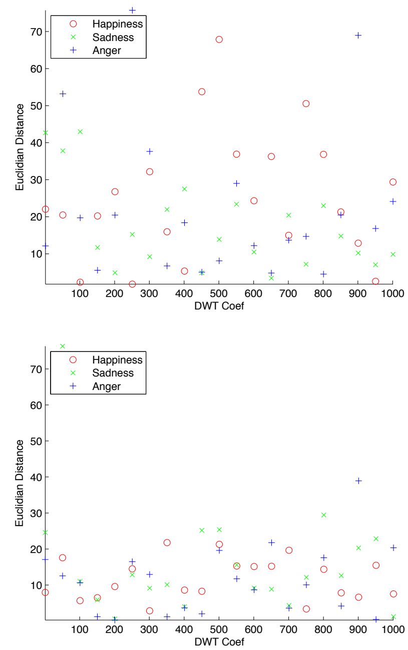

Fig. 5. Dimension reduction from single emotions.

in time for each sample in each of the electrodes and the frequency to create a complete representation as shown in Figure 6 (this model was obtained using EGGlab [15]). In addition to having the ability to perform analysis of signals between multiple users, also produces a good reduction in the measurements of the characteristics and lower dispersion of all the experimental data, the average of this signal is extracted from each of the experiments and correlating each class, since the distribution of emotions in the entire spectrum, is markedly better pooled after multidimensional analysis, as shown in Figure 7.

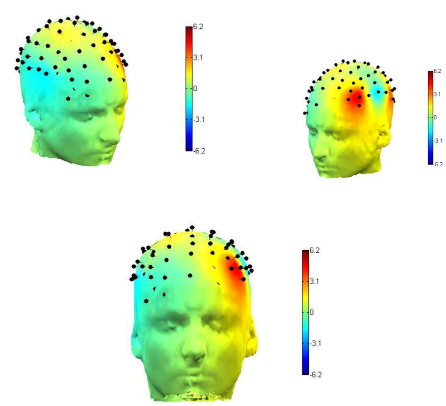

Fig. 6. 10-20 single time analysis, multiple frequency analysis.

VIII. Conclusion

EEG analysis by multiple signals for emotion classification can be a viable option as a system to extract features, because

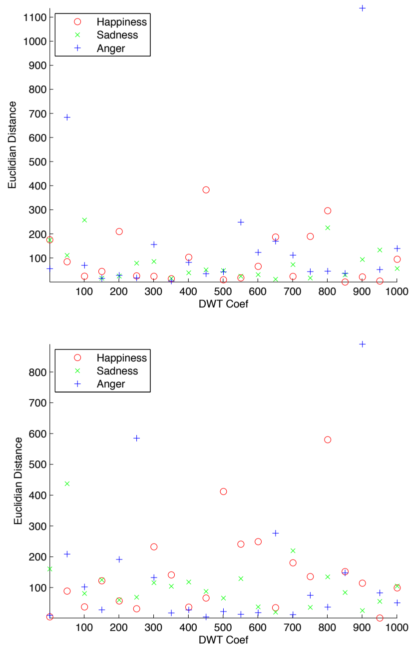

Fig. 7. Maximal and uncorrelated for transformed and transformed set of emotions.

it is very feasible to reduce the computational load involved in the analysis of electrodes at the same time too, as in many other techniques to reduce the number of electrodes, focus attention on the electrodes shown regarding emotional activity in the brain, but these methods do not really know the whole behavior of brain activity that presents certain emotion we could ignore information make it useful for research but this method can be extended to these methodologies and reduce even further the amount of data to classify. A future work could include the detection of emotions more dispersion in AVS or closest emotional states between them that could represent a major challenge, but rather required of the extension of data collection model to explore for minor changes, better resolution is required, implying greater number of electrodes to achieve a better result at the expense of computational complexity this creates another area of opportunity reduction model.

One of the biggest problems in the process of emotion recognition, is the lack of reference databases; Well currently only databases of the international affective digitized sounds (IADS), the basis of International Affective Picture system digitized (IAPS) and bu-3DFE for facials expressions are the only rules in affective research, these rules only provides information to generate experiments (generate information itself) however there is no standard for a database record data with physiological data. To solve this every researcher is the need to generate your own benchmark to be able to realize signal analysis. While this happens, the results can only be valid on the basis of data that a single group or community of researchers and might not be valid from one to another, either unlike poor genres, ages, extraction technique, social situation etc.

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