Emotions characterization over EEG analysis : a survey

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Abstract. This paper presents a review of the emotion characterization, through the analysis of electroencephalogram (EEG) signals and intelligent classifier algorithms. The set of emotions to study are those that are based on basic human survival motivation: *anger, disgust, fear, happiness, surprise and sadness*. In order to achieve the overall vision, topics are addressed as follows. First, an overview of brain computer interfaces (BCI), and a review of previous studies on the evaluation of emotions and their interactions with the environment. Second, a EEG measurement and feature extraction methods based on the implementation of the Wavelet Transform (WT), to rationalize the efficacy of the EEG data to classify the emotions. Finally, the artificial classifiers that allow to perform a characterization of the emotions over a computational models (i.e. Fuzzy C-Means, Neuronal Networks, Support Vector Machines).
Keywords: Emotions, Electroencephalogram (EEG), Wavelets, Artificial classifiers.

1 Introduction

The research of the Brain Computer Interfaces (BCI), like the opportunity to establish a connection between the users and their environment are a very active research area, due the necessity of generate models that can allow to people with some physical illness or mental disorder to interact with their environment more naturally. The main subject on this paper are focused on the fact that the emotions are one of the most important features of the humans, on recent years the research effort in the Human Computer Interaction (HCI), have a particular interest on the humans emotions and the possibility of create a computational model capable to construe human emotions, some of this works are based on the physically reactions generated by the emotions [1] [2], and psychological signal analysis [3].

In the literature, we can find different techniques that allow us to perform assessments to the human emotions activity : Electromyogram (EMG), Electrocardiogram (ECG), Skin Conductive Resistance (SCR),Respiration Rate (RR), Blood volume pressure (BVP),Heart Rate (HR) [3] [5] [8], all this techniques allows to the researches to obtain data based on the physically reaction to the emotions, some of this methods had show results that achieve up to 70-98% of emotion recognition [9], however these results need a high level of environmental control.

Another methods that allow us to monitor the status of the brain activity while the subject are exposed to a emotion, are that ones that monitored the brain activity which are divided in two methods : unicellular register and brain images. The first one uses invasive techniques, which make it a not feasible due the implications that this produces. Otherwise the brain images have a good speed test and gives a good approach to the real data, some of this techniques are: Positron Emission Tomography (PET), Magnetic Resonance (MRI), Functional MRI (fMRI), Electroencephalogram (EEG), Magnetic Electroencephalogram (MEG) and simulation of Transcranial Magnetic Stimulation (TMS). Product of this previous research and methods a relation between the brain activity that are bound to the emotions has been established, however the main difficulty lies in the fact that, it is very hard to uniquely map physiological patterns onto emotion types and the physiological data are very sensitive to artifacts and noises [10].

Exist a great interest on the EEG technique due the feasibility and low cost of his implementation, compared with the others, this technique measured the activity of a group of neuronal cells of the cerebral cortex or scalp, this technique provides physical, physiological and pathological information, which can be analyzed for a medical diagnostic or the research of cognitive processes, with the advantage of not perturb the environment of the test subjects, due that the implementation of the EEG are minimally invasive.

2 Emotions

The emotions are a simple expression that consist on feelings and thoughts but at the same time are subconscious internal processes [11], this processes encompass the daily life and play a key role on it, however the emotions cannot be objectively observed and cannot be measured [10].

As result of the daily experiences we could suggest the emotions as the visible product of another way of thinking, which complement to reason on the daily's decision maker process, based on the perceptions related to the knowledge and the goals, characterized by a trigger and a value [12]. One of the main functions of the emotions are select or provide weight to one or several features from the attention center, and bring a comparative of alternatives in decisions which facilitate the communication.

Emotions involve multiples areas of the brain and shows a complex activation sequences in time. Trough signals measurements the central nervous system provides a relation between physiological changes of emotions and the brain activity [13]. In robotic and virtual agents areas to analyze this situations with a computational approach, exist an agreement of which are the basic emotions, this are the emotions related to survival human motivations, which are listed below: i) Anger: This emotion allow us to prevent that some unwanted situation continues (Right frontal cortex activation). ii)Disgust: Allows us to make a change/or correct something that not contribute to the satisfaction of the needs (Right Prefrontal Cortex Area). iii) Fear: is a defense mechanism to discover the threats (Bilateral Temporal Activation). iv) Happiness: Is a reward that motivates the search (Right Prefrontal Cortex Area). vi) Sadness: This are the manifest of that there's something that need to be satisfied (Left Temporal Areas). The sadness and the happiness involves all most all the brain areas, and also all emotions shares pre-frontal cortex, cingulate gyrus, and temporal cortex areas [11].

Several schemes of emotions classification are defined, all of them shows that a emotion reflects an unique motivational tendency and behavior. This provides the idea of emotions as a very significant part of a system, since they represent unique forms of action related to a physiological patterns [15] [16]. The researchers use this physiological patterns to classify the emotions into three types: (i) Distress (ii) Interest and (iii) Pleasure [17]. Exist many other sets of emotions accepted as the basic sets of basic emotions, i.e. virtual emotions manage like basic emotions, seven basic emotions: Fear, Anger, Joy, Disgust, Acceptance, Anticipation, and Surprise [18], for pattern recognition (linear discriminant) manage four: emotions happiness, sadness, anger, fear and for physiological patterns a set of six emotions defined : happy, sad, disgust, fear, joy and anger and many others[9] [21].

3 EEG Data Acquisitions

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. The recorded wave forms reflect the cortical electrical activity, this provides a frequency that in some literature's are refereed as the rhythmic repetitive activity (in Hz). Related to this the frequency of EEG activity can be classified for it different properties: Rhythmic (EEG activity consisting in waves of approximately constant frequency), Arrhythmic (EEG activity in which no stable rhythms are present), Dysrhythmic (Rhythms and/or patterns of EEG activity that characteristically some disorder).

The frequency content of the EEG signals are the fundamental information to appraising it and is on the 10 Hz where the most significant information are contained [19]. The most common brain signals provides five EEG rhythms that are classified on on table 1, under the premise of a human presents changes of emotions, the frequencies of the activity the brain also present a variations. In fact a individual band of frequency can yield information located on subtle change of emotion [24].

Table 1. Rhythms classifications [24].

$Band$	$Frecuency(Hz)$	$Range(Hz)$
$Delta(\delta)$	.5-4	3.5
$Theta(\theta)$	4-8	4
$Alpha(\alpha)$	8-12	4
$Beta(\beta)$	12-30	18
$Gamma(\gamma)$	> 35	–

Exist also an alpha-like variant called mu (μ) and can be found over the motor cortex (central scalp) that is reduced with movement, or the intention to move for this reason this band are not included in table 1. In the study of the emotions of based on the EEG signal, the alpha (8 Hz 12 Hz) and beta (12 Hz to 30 Hz) bands were highlighted as particular rhythms for recognition.

The arrangement of the placement for scalp electrodes for a EEG plays a important role of recording of the signals, on the recent researches the adoption of the 10-10 international standard system are placed ad the most common electrode placement used by the researchers but there's not a benchmark which indicates a electrodes placement. This standard are a extended version of the 10-20 system of electrode placement as is shown on the Figure 1, also known as the 10% system.

The placement of electrodes is based on landmarks on the skull, namely the nasion (Nz), the inion (Iz), and the left and right pre-auricular points (LPA and RPA). The first step is to form the line from Nz to Iz, approximately over the vertex. To determine the location of the vertex, the contour from LPA to RPA is also passed over the vertex. These two contours should intersect at 50% of their lengths and the point thus obtained is the exact vertex, also exist other proposed the standard for placing the electrodes in various locations at the scalp, and called as 5% system (proportional distances 5% of total length along the contours between skull landmarks), however the use of larger number of electrodes may increase the recognition rate of EEG signal with the cost of compromising physical burden to the subjects and longer time consumption [15].

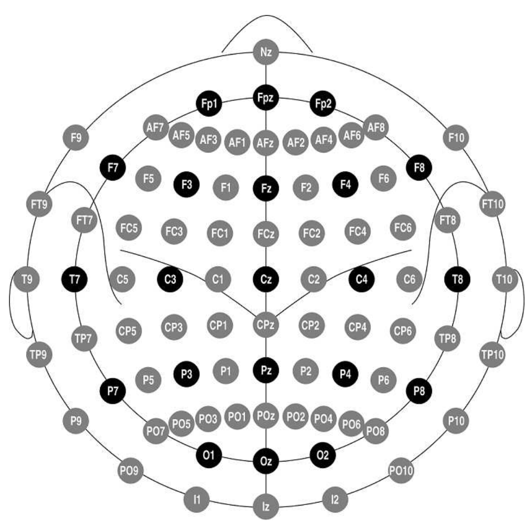

Fig. 1. Electrode positions based on the 10-10 extension of the 10-20 standard [25].

4 Feature Extraction

The electric activity obtained by the EEG, are contaminated with noises generated by the power line and external interfaces, in addition with other kind of signals that aren't product of a brain activity which are known as artifacts (effects produced by the ocular movement and the relation with the brain activity, muscular movements, vascular movements and gloss kinetic artifacts), i.e. previous contributions to identify regular oscillations around 10 Hz to 12 Hz shows that both the alpha (α) rhythm and theta (θ) rhythm are significantly affected by the subject's eye blinking [23] .

The emotion recognition research based on EEG signals, the implementations of non-parametric methods of feature extraction that are based on multi-resolution analysis, on of this method are the Wavelet Transform (WT) [24]. The joint time-frequency resolution obtained by WT makes it as a good candidate for the extraction of details as well as approximations of the signal, which cannot be obtained either by Fast Fourier Transform (FFT) or by Short Time Fourier Transform (STFT), because even though Fourier allow us to obtain a representation of the signal on the frequency, do not provides a time resolution, this means we could know the main frequencies but not in which moment occur, in other case the STFT could solve this problem but is only viable to stationary periodic signals, and like all the most of the biological systems the emotions are non-stationary signals.

Wavelet is a wave limited by a time, which has an average value of zero that allows to describe anomalies, pulses and other events that start and finish within signal that allows analysis time located in a large signal, providing the possibility of encountering discontinuities or peaks of short duration that would otherwise, it would be difficult to detect and treat and this technique are a based on spectral estimation where we can express any general function that can be expressed on a infinite series of wavelets. The idea of this function is represented as a linear combination of a particular set of functions, obtained by translating and scaling of a basic function called mother wavelet ($\Psi_{a,b}$).

For this kind of signals the $\Psi_{a,b}$ is given as

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

Where $_{a,b} \in R,_a > 0$, R is the wavelet space.

The parameters "a" are the scaling factor and "b" are the shifting factor, by selecting a suitable scaling values and a time offset for a wavelet it can be established like a effective method to analyze a non stationary bio-metrical signals [22]. The WT are then obtained by the internal multiplication of *f(t)* with the wavelet function.

$$W_f(a,b) = \{f(t), \Psi_{a,b}(t)\} \tag{2}$$

This transform reflects the state of the function on *f(t)* on the scale (frequency) and the position (time). The only limitation for chose a prototype as a mother wavelet is to satisfy the admissibility condition.

$$C_\Psi = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{\omega} d(\omega) < \infty \tag{3}$$

Where the $\Psi(\omega)$ is the Fourier transform of $\Psi_{a,b}(t)$.

The time-frequency representation is performed by repeatedly filtering the signal with a pair of filters that cut the frequency domain in the middle, this means that WT decomposes the signal into approximation coefficients (CA) and detailed coefficients (CD). The approximation coefficient is subsequently divided into new approximation and detailed coefficients. This process is carried out iterates and producing a set of approximation coefficients with detail coefficients at different levels or scales as we can appreciate on table 2 [24] [38].

Table 2. Decomposition of EEG signals into different frequency [24].

$Band$	$Frecuency\ Range(Hz)$	$Decomposition\ Level$
$Delta(\delta)$	0-4	D6
$Theta(\theta)$	4-8	D5
$Alpha(\alpha)$	8-14	D4
$Beta(\beta)$	14-32	D3
$Gamma(\gamma)$	32-64	D2
$Noises)$	64-128	D1

There's another method to filter the signal based on the of Surface Laplacian (SL) filter for removing the noises and artifacts (Eq. 4). The SL filter is used to emphasize the electric activities and filtering out those that might have an origin outside the skull, however this method could lose various spatial frequencies from the middle frequencies which could be a potentially useful information.

$$X_{new} = X(t) - \frac{1}{N_E}\sum_{i=1}^{N_E} X_i(t) \tag{4}$$

By now we can divide the feature extraction techniques as: Time Domain Analysis, Frequency Domain Analysis and Time-Frequency Analysis, however also exist two other methods for feature extraction: Fractal Analysis and Interval Analysis, the first are a new scientific paradigm that has been successfully used in quantifying the complexity of dynamical signals in biology and medicine[26]. The intervals analysis is also widely accepted due to its simplicity and usefulness, but is not sensitive to the noises and other artifacts [27].

5 Emotion Classification

Recognize a emotional state based on analyze the features from inputs with a good accuracy, are one of the main goals of the emotions recognition, to achieve this the time taken for training through an intelligent method are a important factor for emotions classification. Many techniques to perform the classification can be used, i.e. Support Vector Machines (SVM), Neural Networks (NN), Linear Discriminant Analysis (LDA), Multi Layer Perceptron Network (MLPN), Naïve Bayes Classifier (NBC), Fisher Discriminant Analysis(FDA), Binary Fisher Discriminant Analysis (BFDA), Transferable Belief Model (TBM) and many others. The table 3, shows the previous researches made to achieve the emotions recognition by the analysis of the brain signals and intelligent classifiers.

The actual researches are focused to provide a better interpretation from the correlation between emotions and brainwaves are growing with the main goal of create BCI applications, nevertheless only few results add conclusions which correlate the EEG with particular emotion. In correlation with the filters and the classifiers, the use of visual, audio or audio-visual stimuli to provoke emotions, plays a very important role. Which are used to intentionally create lab settings based on exposing to the subject to a selected emotional images from the international standard data bases to obtain brainwaves of a desired emotions.

The intensity of the emotion experienced by the subjects during the experimental analysis with audio-visual stimuli provoke much better results compared the other two stimulus methods (audio or visual)[10]. In the same panorama the consideration of use statistical features to classify emotions are implemented too, such as mean, standard deviation, power, variance and Analysis of Variance (ANOVA).

Other thing to note in table 3, is that the valence-arousal based on two dimensional analysis of emotion classification is discussed in majority of works, and that the neural network and LDA methods have higher classification rate than other classification methods such as SVM, Linear Mapping (LM), and LBC classifiers as can be observed on table 3. A recognition accuracy of over 90% of average seems to be acceptable for realistic applications and actual research findings suggest this are possible and brainwaves can be successfully identified using statistical features [15]. In general, the assessment of human emotions with greater accuracy is depends on number of electrodes, placement of electrodes, method of pre-processing and feature extraction used for emotion detection.

Since the classification methods depends on grouping the unknown data by previous learning process[15]. A large amount of researchers tend to use lesser number of electrodes for recording EEG signals, most of the electrodes are placed on the region of frontal lobe and parietal lobes are considered for acquiring the EEG. In addition, there is no standard benchmark available to select the number of electrodes and location of electrodes in human scalp for emotion recognition applications [24].

6 Conclusion

A significant amount of investigators have dealt researches for determining the best methodology to obtain a acceptable classification accuracy. However since,the EEG patterns are different for each person, a set of interdisciplinary and collaborative works are required for concluding some significant results. Other aspect to note is, that only a few researchers have discussed about the effects of multiple emotions on given stimuli, generating on this is one of the important area to research since, as we know multiple emotions under natural conditions could occur and are not stationary which mean that a state of a emotion may vary in time.

To reach the goal of classify emotions on efficient way, a several further studies are required to analyze the relation between brain waves and the effect of multiple emotions,coupled with this a development of more efficient pre-processing and feature ex-

Table 3. Review of the implementation of artificial classifiers for emotion recognition

Classification Method	Summary
Support Vector Machines (SVM)	*The classification of EEG signals for BCI applications through adaptive learning and co-variance matrices with adaptive learning and Common Spatial Patterns (CSP). Classification Average : 70-76%* [28].
SVM	*Recognition of five emotions (joy, anger, sadness, fear, and relax) through multi-modal bio-potential Signals. Classification Average : 41.7 %* [3].
MLPN	*Recognition of four emotions (angry, sadness, pleasure, and joy) have been classified using MLP network. Classification Average : 69.69%* [29].
BFDA	*PCA is applied for feature selection and emotion is classified in two dimensional axis that means alpha and beta band power and power ratio between alpha and beta band. Classification Average: 90%* [30].
SVM + NN	*Estimation of two emotions (Pleasure and unpleasure) by the classification using NN and SVM. Classification Average : 62.3 %* [31].
LDA + NN	*Estimation of five human emotions (joy, anger, relaxation, sadness, and worry) using fractal- dimension of EEG is classified using NN and Linear mapping network* [32].
FDA + NBC	*Estimation of emotions in two dimensional space is detected, with the power at six frequency bands. Classification Average : 54 - 55 %* [33].
NBC + SVM + NN	*Emotions are classified in valence-arousal space using three classifiers, using the frequency band power, Cross correlation coefficients, Peak frequency in alpha and beta band, and Hjorth parameters. Classification Average : 29% - 35%* [34].
Transferable Belief Model(TBM)	*Estimation of two emotions (Positive -happy- and negative emotions-sad-) are detected, by using the patterns of the energies at various frequency bands of EEG signal, and power at selected frequency bands.* [35].
Mean, Analysis of Variance, Standard deviation	*Estimation of three emotions (pleasant, aversive, and neutral) are classified according features such as mean, standard deviation, power, variance and Analysis of Variance* [36].
Multivariate Analysis of Variance (MANOVA)	*Recognition of (depressed or Non-depressed) emotions derived through MANOVA* [37].
Fuzzy C-Means Clustering (FCM)	*Measures Emotions using EEG signals on classifying human emotions using fuzzy c-means clustering for Wavelets, based on minimizing : Fuzziness Performance Index (FPI), Modified Partition Entropy (MPE) and Separable Distance (SD). In addition, the Objective Function Value (OFV) is also considered as a measure for classifying emotions* [10].
LDA + K Nearest Neighbor (KNN)	*Classification of emotions divided on subsets (disgust, happy, surprice, fear and neutral), whit a maximum subsets of emotions classification rate of 91.67% for disgust, 81.67% for happy and surprise, 81.25% for fear and 93.75% for neutral is achieved using 62 channels EEG signals* [24].

traction methods are required to. Also, further studies are required to select the number of electrodes and the placement of electrodes on brain region due to these are essential to obtain valuable information in the emotion recognition. Furthermore there is no comparative study has been possible by determining the statistical correlation between different emotions and EEG signals. Also a factor to empathize are the applications of this methods to help people with some illness, by the development on systems that can help them to interact them on a more natural way.

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