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Emotion analysis through physiological measurements

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Abstract. There have been several advances in the field of affective computing analysis, however one of the main objectives of the brain computer interfaces (BCI), it is to interact in a natural way between human and machines; The analysis of the emotional state user is very important since it may provide a more suitable interaction generating closest approach, and efficient interaction. Furthermore extent that implementation of systems that can develope an emotional human-machine interface, applications of affective computing, it could widely used to help people with physical or deliberately to analyze and characterize the emotions that may be of interest and provide benefits on a human activity (eg, performance of athletes).

In this paper seven emotional related experiments where development according whit the model arousal / valence model, each experiment corresponds to an evoked emotion from 32 study subjects and contains information the galvanic skin response (GSR), an electrooculogram (EOG) and electromyogram (EMG), for each user, each emotion is evoked by a process audio / visual for 60 seconds, focused generate three emotions (anger, happiness, sadness). Statistical measures are used to create parameters and distances to generate an overview of classification of signals related to an emotion. For information preprocessing is used discrete wavelet transform and statistical parameters (mean, standard deviation, variance) plus a surface filter.

Keywords. emotions, affective computing, physiological, Discrete wavelet transform

Introduction

Computers play an important role in the behavior of users and interactive with the world, however the machines lack of sympathy or interest in the interaction with the user, in recent years the increasing development in mobile technology and the development of increasingly targeted applications to the user, have facilitated the development of applications that generate most natural interaction between the device and the user. Taking advantage of this with the flexibility that hardware design and development have been presented with the increasing accessibility of the costs, the field of human-machine interfaces (HCI) emerged to create a new class of interfaces that allow you to interact with a device in a more natural way, by the analysis of signals collected from a user through

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sensors. Currently the technology would allow us to generate models to facilitate empathy in human-computer interaction and development of artificial systems built to interact in a more natural user through mobile devices [1]. Modeling and emotional status classifications for this purpose are the main areas to develop, which in turn would lead to a less state of user frustration when interacting with new technologies.

Psychophysiological signals for this case we are useful in the detection of mental and physical state associated with a cognitive and/or emotional. The processing and analysis of physiological signals through sensors presents a wide range of possibilities, particularly the development of systems that allow us to know the emotional state and take action to correct default either way the device communicates with the user custom or create an environment that benefits the emotional state (eg color changing system environment or creating musical environments based on user preferences) [2].

1. Emotions

One of the main problems in the analysis of emotions is itself the complexity of the concept of emotion, but most researchers agree that emotions are acute affective states that exist in a relatively short period of time and that are related to a particular event, to an object or action [2] [3]. In conjunction with this in psychology, emotions are predominantly described as points in a two dimensional space of valence and arousal model (VAM). This allows us to generate broad categories of emotions, to differentiate between high and low high and low valence or arousal. However, in principle an infinite number of categories can be defined, because the valence and arousal are not necessarily linked is not directly proportional to each other [4] [5] [6] . Although this can not be represented in the VAM, it provide a representation of how it could represent the mixture of emotions as it contains positive and negative at the same time fastened a Cartesian representation.

The VAM allows better discrimination between different emotions. In this work, only three emotions where analyzed selected because are evenly distributed in each quadrant from the Russel model, in the form of high valence high arousal for happiness, low valence arousal such as anger and low valence / low arousal as sadness, as shown in figure 1 . The quadrant high valence and low arousal emotions are related reserve for the state of relaxation and was taken as a reference point and to calculate the metric between the distances between an emotion regarding other statistical characteristics.

2. Methodology

2.1. DEAP Database

Another important problematic in the development and research of behavior and emotional recognition, is the lack of benchmarks measures related to physical or emotional reactions, currently only the IADS (audio / sound), IAPS (visual / image) and BU-3DFE (Inghamton University 3D facial Expression), are to our best knowledge databases generate responses related to emotions in users, however do not contain emotional information of a set of individuals to serve as reference for future research. Another important reference database is DEAP Dataset (-Database for Emotion Analysis Using physiological

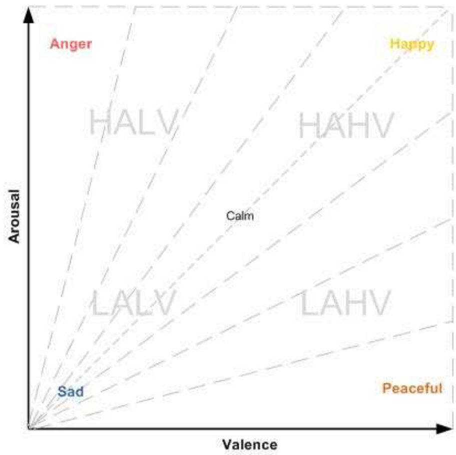

Figure 1. VAM bi dimensional representation for emotions

signals), which is to our best knowledge the most comprehensive database, for collecting survey-based information and generates a wide variety of emotions using technical audio visual, online surveys and information subject status at the time of study realizase the experiment also includes psychological as well as physiological signals plus a video recording of members while performing the experiment [1].

As mentioned in section 1, it is necessary that the space can be divided to be characterized and the DEAP database VAM can be subdivided into four quadrants, low arousal / low valence (LALV), low arousal / high valence (LAHV), high valence / low arousal and high arousal / high valence (HAHV). With the order to ensure diversity of emotions induced [7], an important aspect to highlight on this basis of data is that could be employed as reference of other investigations and other members where conditions of the experimentation could or not be diverse.

2.2. Physiological Measurements

On [8] have shown that the physiological characteristics are altered naturally in the presence of emotions (eg, heart rate, blood pressure, respiratory rate, the galvanic skin response, brain activity and muscle activity tend to suffer variations to be influenced by any emotion). Besides physiological signals are in many cases autonomous and the system that controls this are regularly outside of conscious control of a subject [10].

To properly generate information about emotions in a lab, is necessary to consider create a space with no discomfort and present a good characterization of the experiment one of the most important. But also one of the important aspects is the correct interpretation of the signals, based on the type of experience provided to people and settings control to detect emotional states, this means you have to develop a robust interpretation algorithm signal, which take into account the induced emotion and the reaction of the user in a spatio-temporal process.

However, a system will only be able to determine the emotional state of a user, only if this involves monitoring psycho-physiological measurements in real time in order to create a profile of a user and because the devices to assess direct physiological measures are often considered to be annoying to the user, which created incorrect or unreliable measurements for analysis, which implies that the simple fact of the study involved in this change. In the affective computing field, there have been some efforts to design discrete measurement technology, known as affective wearable [9], defined these as tolerant systems and the use of sensors and tools to recognition with the least possible interference. This allows us to considerations emotions measurements could be made, particularly for this experiment the following physiological measurements were considered:

- Galvanic Skin Response (GSR).
- Electrooculogram (EOG).
- Electromyography (EMG).

In galvanic skin response (GSR), also often referred to electrodermal activity [10], which is a measure of the conductivity of the skin which represents the influence of the sweat glands under more excitation it produce more sweat, consequently increase the conductivity of the skin. The GSR was chosen because it is a measurement that can be unevaluated by a peripheral, easy to handle and this activity can not be easily controlled by the user. GSR is calculated from the measured signal with a time constant of about 63 seconds per experiment, in this time window are captured GSR signal variations. According to peripheral physiological sensor placement in [1], four electrodes are used to record EMG EOG and four (the zygomatic major and trapezius muscles).

We measure muscle movement using an electromyogram and electrooculogram, which have been shown to undergo alterations individually in the presence of emotions such as stress or surprise [7] [11]. The electrooculogram, relies on the eye-blinking affected by emotional state, and the results are reflected in easily detectable peaks in the signal (eg the rate of eye blinking is another feature, which is correlated with anxiety as a process for the psycho-physiology of emotion) [12] [14], features that could be analyzed for the eye blink rate are energy, mean and variance signal. Electromyography in muscle activity can also be assessed in frequency therefore EMG signals which are a generalization of the muscle action, and found the existence of variations activity peaks enegia or most of the power in the spectrum an EMG during muscle contraction is in the frequency range of 4 to 40 Hz.

2.3. Experiment development

Once defined the parameters to be analyzed and generated the abstractions necessary to carry out the analysis, information is made up as follows:

- Raw information.
- Filtering: implement a notch filter from 3.5 to 47.5 Hz and a filter surface (1).
- Wavelet processing: use a wavelet Daubechies 6 to level 3 to multiple signals to generate a signal characteristic.
- Extraction of features: calculate the transform coefficients and store them in an array.
- Statistical analysis: developing statistical calculations of the coefficients of the Transformed (mean, standard deviation, variance).
- Calculate metrics of an emotion to another emotion: calculated based on a euclidean metric distances.
- Deploy and calculate results: graph and calculate results for each statistical data for each user and for each experiment.

3. Feature extraction

Due that a very large amount information would be proceeded at the same time a data reduction and pre-procesing task most be performed, to avoid to compute unnecessary data.

3.1. Pre-processing

In the analysis of the signal is necessary to consider the noise, to prevent the loss of potentially useful information, you need to apply filters that allow us to eliminate unwanted information of the experiment, for this analysis was implemented a Laplace filter surface.[15].

The mathematical model of the filter is given as:

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

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

3.2. Wavelet Transform Analysis

Due to the nature of the signal that is being analyzed and is a biological signal that changes over time the use of the Fourier transform (FT) is inconvenient, because although we can analyze the signal in the domain of the often only possible to analyze the frequency spectrum as a whole without knowing the time of occurrence of each. To resolve this issue, the Short Time Fourier Transform (STFT) can be used, because this transformation maps a time signal into a two-dimensional signal time and frequency, however the drawback is that only the STFT can be known frequency signal comprising the small time windows and the total spectrum or unknown behavior of the signal as time advances.

Often there is a need for better resolution in time at higher frequencies, the wavelet transform is able to cope with this requirement, even though mapping the signal into timescale or time-frequency, because perform a connection between scale, level and frequency. Due that we are working with a biological signal and there is need for time resolution of the frequencies, the implementation of the wavelet transform is desirable since it is able to cope with this requirement, since it is able to perform a mapping of signal time scale. The wavelet transform and its characteristics render it the most appropriate for analyzing this type of a non-stationary signals, based on the expansion and recruitment right through signals and displacement of a single function prototype (ψa,b, the mother wavelet), specifically selected for the signal under consideration.

The mother wavelet function $\Psi_{a,b}(t)$ is give as:

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

where $a, b \in R, a > 0$, where R are the wavelet space.

Parameters a and b are the scaling factor and shifting factor respectively. The only limitation for choosing a prototype function as mother wavelet is to satisfy the admissibility condition:

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

Where $\Psi(\omega)$ are the FT of $\Psi a, b(t)$, the time-frequency representation is done by filtering the signal several times with a pair of filters to divide the frequency in half additionally, at each level of decomposition. Decomposes to transform approximation coefficients (CA) and the detailed coefficients (CD). Turn on each iteration the approximation ratio is then divided, into new approximation and detail coefficients.[13] as show on figure 2 and figure 3, where the continuous and discrete analysis where performed it respectively; Figure 2, shows the statistical measurements (mean ans standard deviation) from the reconstructions coefficients over a 63 seconds signal with a continuous wavelet transform analysis, from a single GSR electrode(sensor), and the Welch scalogram that provides the spectral density from the energy over time. On figure 3, the same signal where analyzed with a discrete wavelet transform, an approximation reconstruction where performed to generate a better perspective of how efficient this method could thread this kind of signals with the half of samples from the signal, however we know that continuous wavelet transform are not suitable for real implementation it gives us a good idea of the signal behavior .

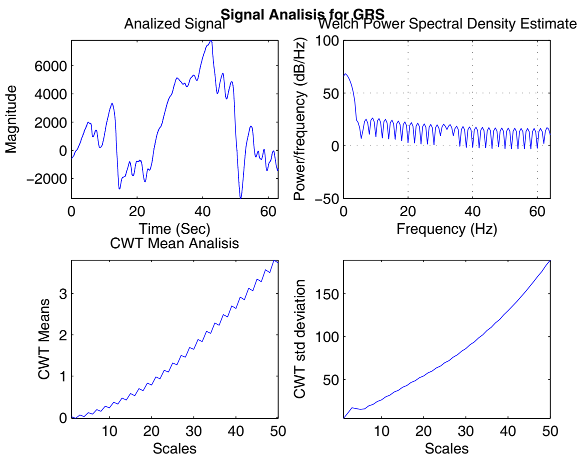

Figure 2. Continuous Wavelet features analysis

3.3. Data reduction

In order to be capable of compute the physiological measurements on efficient time the multi-signal wavelet analysis was made and work with the statistical measurement for the reconstructions coefficients of the wavelet kernel.

- Laplacean Filter : Remove all the baseline noise and smooth the signal.

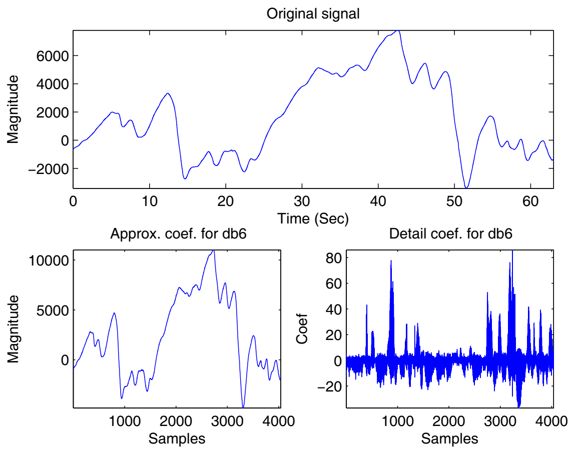

Figure 3. Discrete Wavelet features analysis

- Band-pass Filter: All samples, number of local minim in the GSR signal, average rising time of the GSR signal, 10 spectral power in the [0-2.4]Hz bands, zero crossing rate of Skin conductance slow response (SCSR) [0-0.2]Hz, zero crossing rate of Skin conductance very slow response (SCVSR) [0-0.08]Hz, SCSR and SCVSR mean of peaks magnitude as on [7].
- Wavelet Transform: Transform the signal using DWT, with a Daubechies 6 at level 3 to perform the characteristics extraction.
- Coefficient statistical measurements: Mean, Standard Deviation, Median and Variance where used to perform the grouping of the signals for each related emotion.

4. Results

Analysis for dimension reduction shows a remarkable relationship between anger and sadness for experiments GSR measurements, as can be seen easily in Figure 4 and 5, where the left plot shows the performance of the three emotions with respect that rate behavior over time. This clearly shows a trend in the behavior of the measures taken to emotion and as shown in the other graph the distance between sadness and happiness can be seen in a more clear, also in figure 5 the measurements and distances between emotions can be observed in reference with another for each other emotions.

Moreover, these results are only for GSR analysis, where the trend of anger and sadness has a very similar behavior, as shown in Table 1. However, in figure 6, the analysis of EOG for the same three emotions is observed that the behavior of happy and sad emotions seem to be more related, which is the same case for behavioral results on the analysis of EMG characteristics, as shown in figure 7, where the first sight, anger and sadness tend to behave more like, however as can be seen in Table 2, the percentage of similarity shows that emotions are sadness and happiness a more similar (a close up view of these two emotions tend to have a more stable and anger grows as $x = y$, function).

GRS Stadistical Measurements	Sad-Anger (%)	Anger-Happy (%)	Happy-Sad (%)
Mean	68	32	25
Variance	73	26	23
Standar Deviation	75	28	28

Table 1. Similitude from statistical measures of coefficients for GSR (rounded up)

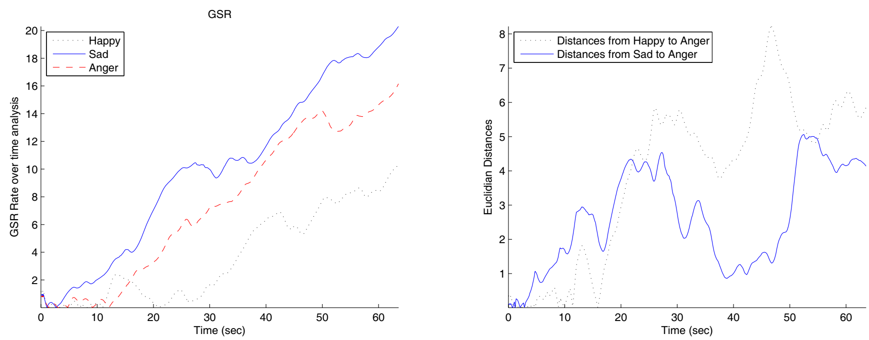

Figure 4. GRS Emotions behavior and distance

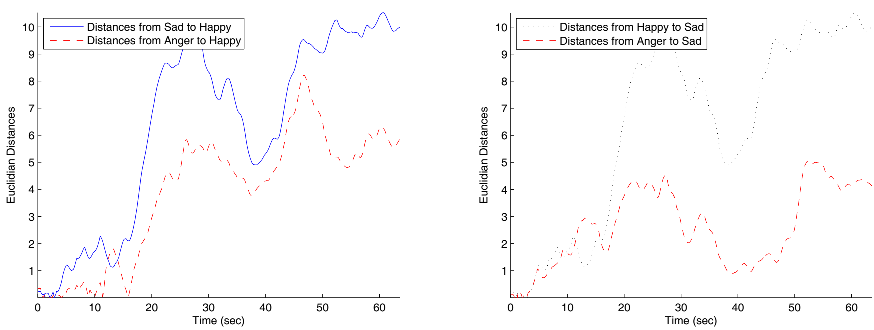

Figure 5. GRS Emotions distance

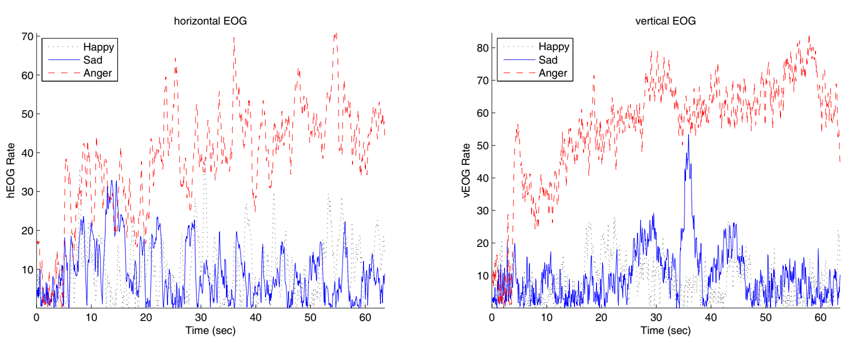

Figure 6. EOG emotions behavior

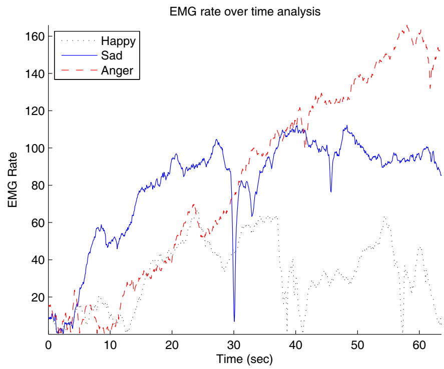

Figure 7. EMG emotions behavior

EOG Stadistical Measurements	Sad-Anger (%)	Anger-Happy (%)	Happy-Sad (%)
Mean	32	34	77
Variance	30	36	75
Standar Deviation	28	38	79
EOG Stadistical Measurements			
Mean	25	19	85
Variance	23	15	87
Standar Deviation	24	20	85

Table 2. Similitude from statistical measures of coefficients for EOG and EMG (rounded up)

5. Conclusions

A close similarity has been found in the emotions of sadness and happiness, however as one of the mayor issues in the process of emotion recognition is the lack of reference, since at present the IADS (audio / sound), IAPS (visual / image) and BU-3DFE (Inghamton University 3D facial Expression), are some of the most common databases to analyze, it exists as a benchmark to compare results, which creates the need to generate a point reference to improve emotional research on physiological processes. As this occurs, the results can only be valid on the basis of data that a single group or set of researchers and may not be valid between one and another.

On the other hand using wavelet analysis as demonstrated offers researchers a superior alternative and viable for the analysis of biological signals related to an emotion, the use of wavelet analysis provides a greater power to resolve transient events and a range of simultaneous frequency in this case.

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