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Emotional analysis thru EEG signals, to monitor high performance athletes

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Abstract. *Emotions play a very important role in our daily life as well as in people's behavior in various situations. Emotions act as a set of rules in the decision making process that dictates a subject's behavior, i.e. the way a person reacts to the same situation but in a different emotional state (e.g. if the subject reacts anxious, elated, aggressive or friendly to the same stimulus), this situation also affects an individual's work performance, recreational and sports activities as well as social interactions. This article focuses on the possibility of increasing athletic performance by analyzing and monitoring the emotional state of an athlete through physiological measurements, specifically electroencephalogram (EEG) analysis as a methodology for brain waves recording using techniques such as spatial and temporal wavelet in order to calculate the similarity in brain activity behavior and brain activation bands to differentiate activity characteristics from one emotion to another. This work also has the purpose of creating a computational tool to help make decisions in an early and timely manner, before various situations may affect the performance of an athlete.*
Keywords: emotion, electroencephalogram, emotional and physical performance.

1. Introduction

One of the main problems in emotion analysis is the concept complexity of emotion itself, however for most researchers emotions are affective states that exist in a relatively short period of time and regularly are related to an event, object or action in particular. Emotions are usually, but not only, described as ordered pairs on a bi-dimensional space, the valence level and arousal level dimensions, the valence represents in general terms that describe the level or value of experiences, such as defining the emotional states that are perceived as negative or positive, the arousal indicates the activation degree of an emotion, (i.e. the depth with which you get an emotion). This bi-dimensional representation is allowing us to establish difference between general emotions categories and emotions in particular by providing difference ranges between high and low valence and between high and low arousal. However, this is a linearly scaled model; primarily an infinite number of emotional states could be defined between one emotion and another, because the arousal and valence levels are not proportionally linked. The current paper is divided into the following sections; section 2 shows the study problematic of emotions and other related work, section 3 shows the model's experimentation reference system, its analysis and results; and section 4 addresses the findings, discussions and future work.

2. Background and related work

An important issue to address is the development of brain computer interfaces (BCI's), specialized in providing the emotional state of a person and provide possible solutions (basing on a user profile), in order to prevent or encourage the behavior associated with an emotional state. This application could help take corrective action in situations that could affect the performance of an athlete in competition, by recognizing whether there are adverse emotional conditions before each competition, on the other hand it can also be used to track the athletes training and identify their mood as well as the conditions that may affect the development of their skills. Currently emotional analysis is performed through the application of psychological tests and surveys or a mixture of both techniques, but the results interpretation is merely a decision of an expert in the area. The analysis of brain activity by BCI is intended to provide an acceptable level of resolution based on data registration and level of similarity calculation. For this to be feasible it must achieve a minimum 90% level of recognition and specifically recognize emotional states [1]. The AVS must be able to distribute evenly all emotions in a coordinate space shown in Figure 1, using a quadrant distribution for arousal and valence scales.

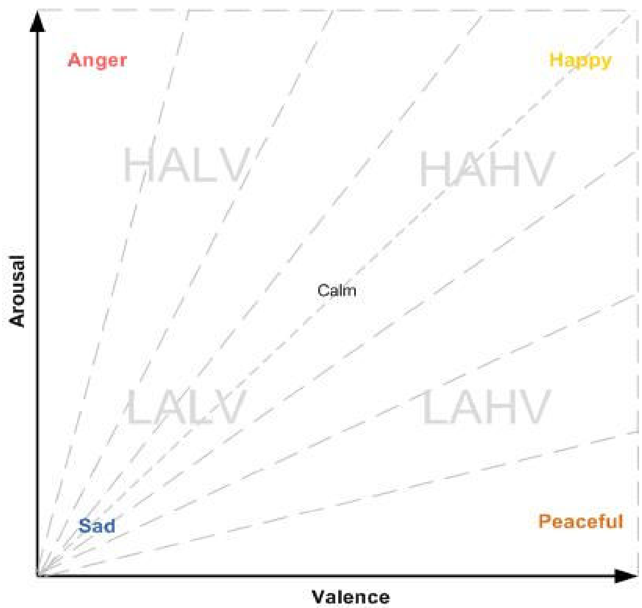

Figure 1. Arousal-Valence Space with four distributed emotions.

HAHV (High Arousal – High Valence), HALV (High Arousal – Low Valence), LAHV (Low Arousal – High Valence), LALV (Low Arousal – Low Valence).

The reason for considering the use of EEG analysis over other techniques is that nowadays there are two techniques to study brain activity known as invasive and noninvasive techniques [2]. Invasive techniques require a high temperature control and specialized clinical skills in addition to disrupting unwanted physiological study subjects, so that such techniques are not feasible for most research projects, noninvasive techniques on the other hand do not require clinical intervention and high temperature control, therefore the use of a noninvasive technique is a better option, however there are several techniques for analyzing cerebral activity such as: the magnetic resonance imaging (MRI), electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), magneto-electroencephalography (MEG) and positron emission tomography (PET). However, although these techniques are non-invasive MEG, PET, fMRI, is technically demanding and expensive, which make these techniques impractical for widespread. In this scenario, the EEG is the most feasible to implement mainly because it is relatively inexpensive to implement as it doesn't require a clinical setting or a controlled environment and needs a low level of technical knowledge [3].

To date, several researchers have developed work related to the analysis of emotions or computing affective, however most of the research that was developed is focused on the BCI's, specializing in helping people with physiological conditions or limitations as well as for people with diseases limiting the cognitive process, however in the area of human machine interface interaction, developments have centered on creating a more natural interaction between a user of a device. To our best knowledge, there is no work on the implementation of both philosophies and develop a system for the brain waves analysis, and a specialized interface to generate a diagnosis that can be used to prevent adverse situations. Mainly this analysis is focused on the emotional analysis of high-performance athletes, in order to develop specialized digital emotions record [3, 4, 5].

Within the same context for the analysis in affective computing brain behavior, we have developed two main methods called: Techniques evocation (induced techniques) and imaginary engine models. The technique of evoked stimuli, external stimuli using either visual, auditory or visual audio to provoke a specific emotion; imaginary engine models, using the memory of a subject of study in which you are asked to recall an event in his life that is related to an emotion, a variant of this technique is the hardware system control that has also generated good results in which the subject is asked to think about moving a body part and analyze the activity brain that this generates [6, 7, 8].

3. Experiment

For this experiment we performed brain activity analysis to 24 study subjects (12 women, 12 men), all right-handed. It was used an evocation of emotions technique in which 40 visual audio stimuli were presented chosen from the IADS (affective auditory stimuli) [9] and the IAPS (affective visual stimuli) [10] to induce emotions of sadness, anger and happiness, for each of the emotions evoked was kept a log by a minute.

3.1 Experimental considerations

Several considerations has to be made, due that the EEG signals need to be preprocessed in order to avoid useless information that could cause incorrect measurements.

3.1.1 Noise and Electrode arrangement

In the signals analysis also need to consider the noise added by environment and other physical activity that could be recorded, that generally tends to the loss of potentially useful information, this requires the application of filters help the experiment to eliminate unwanted information signals. It was applied Laplacian filter surface and a notch filter passband from 3.5 to 47 Hz, and the placement of the EEG electrodes is performed according to the model 10 - 10 [11], 64 electrodes, as shown in Figure 2.

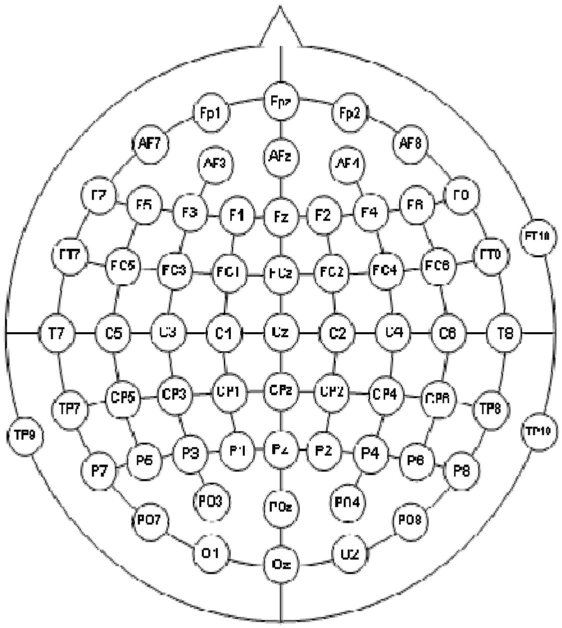

Figure 2. 10% electrode placement for EEG analysis [11]

3.2 EEG Signal processing

Due to physiological signals are non-stationary, the classic Fourier analysis would not be suitable to provide adequate performance for this type of analysis, since it only provides the signal frequency spectrum of across the time spectrum, this means that if you want to know when a specific frequency is produced using this technique it will not be able to provide this information, this problem could be solved by the Fourier transform as it provides a window in time which contains all information frequencies occurring between two time slots, however this technique does not provide the entire spectrum of signals and one of the most important aspects in the analysis of signals emotional processes, the study of brain rhythms. In neurology rhythms are called frequency bands of the brain and are defined as: delta rhythm (0.2-3.5 Hz), theta (3.5-7.5 Hz), alpha rhythm (7,5 - 13Hz), beta rhythms (13-28Hz) and gamma rhythm (> 28 Hz) [12]. To solve this problem, a temporary space analysis is needed and the wavelet transform is a great candidate to analyze these signals.

3.2.2 Wavelet Transform

The wavelet transform is a technique for analyzing the time-frequency signal, this means it can provide resolution of time and frequency of a signal in a single representation. For more information on this technique, you can review these references [13, 14].

3.3 Emotional signal analysis

Statistical analysis of the signals magnitudes were taken to represent the behavior between an emotion and another, creating characterization of an emotion, based on the response of the brain signals. This can be interpreted as the calculation of distances average associated with the behavior of the signal up on anger, sadness and happiness. These distances provide parameters to identify emotions and ranges for classifying them, i.e. once the signal is processed statistical calculations are made of the signal behavior and then are compared to records that already have of each emotion, the signal can be characterized as part of the data set with which it is a shorter distance that generate a common region of the increasing brain signal behavior, to determine each emotion.

3.4 Signal measurements and results

The behavior in the time and frequency of the signals is analyzed and the results were distributed as shown in Figure 3, 4, and 5, using one emotion as a reference in each one, the distances are obtained by calculating the Euclidean distances (Eq. 1).

$$x = \sqrt{(a-b)^2} \tag{1}$$

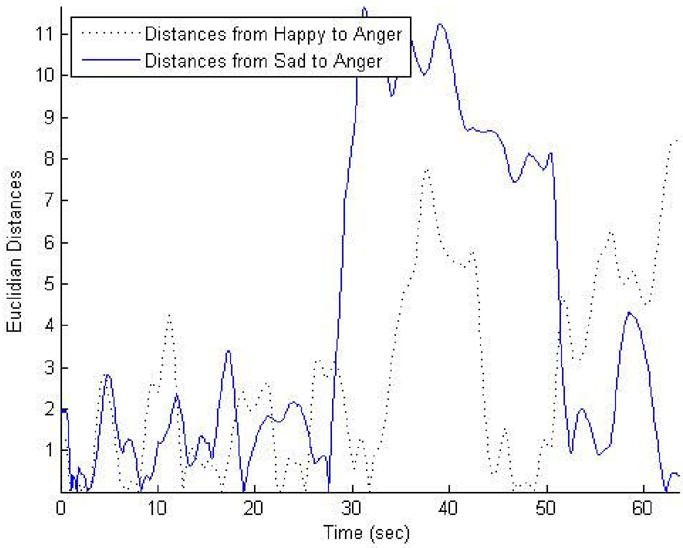

Figure 3. Euclidian distance from sad and happy emotions respect to anger.

In Figure 3, the distances between anger and happiness are noticeably smaller than the distances between anger and sadness; this is most noticeable in the time window of 30-50 seconds. This overall result can be better observed in Table 1 and Figure 6, which shows a numerical analysis of the overall average distance of the signal behavior between an emotion and one for each possible permutation of the three emotions.

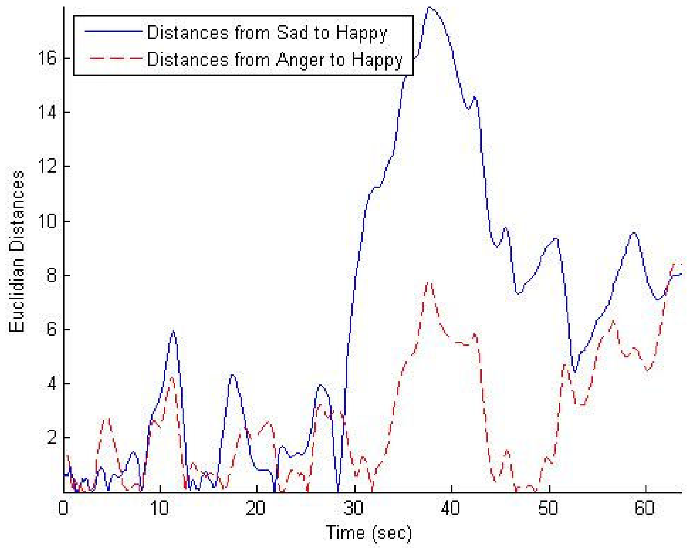

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Figure 4. Euclidian distance from sad and happy emotions respect to happy.

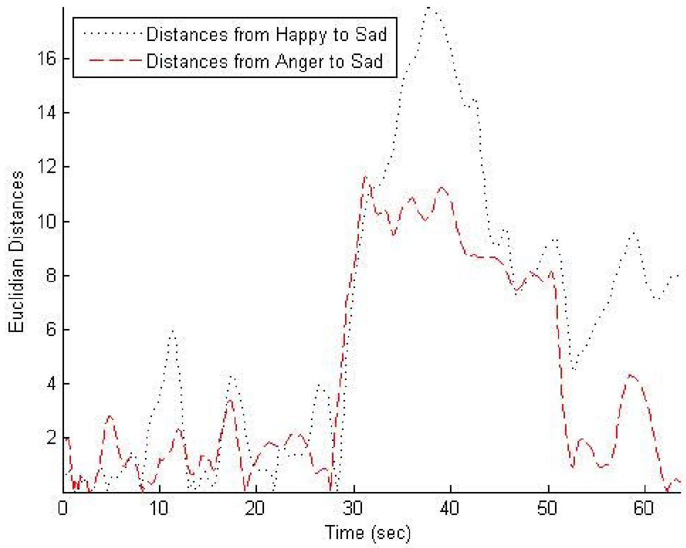

Figure 5. Euclidian distance from sad and happy emotions respect to sad.

Emotion	Anger(Euclidian distance)	Sad (Euclidian distance)
Anger	0	5.08
Sad	5.08	0
Happy	4.58	6.34

Table 1. Comparative of average distance from the magnitude for single emotions.

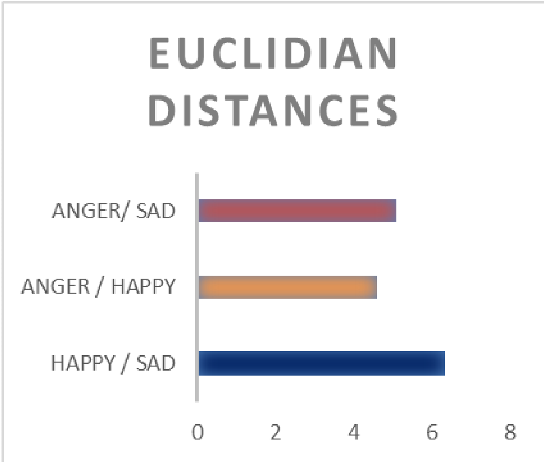

Figure 6. Euclidian distances from the variance of the wavelet coefficients.

4. Conclusions

Actual results only provide information about the close relationship between brain activity generated by two emotions, which are anger and sadness, but in spite of that happiness has less distance which involves greater difficulty discerning their behavior, provides a good separation for the implementation of intelligent classification algorithms and grouping of classes as the algorithm of k-NN (k-nearest neighbor), Bayesian analysis, Fisher discriminant analysis and support vector machines (SVM), which are technically already previously used by some researchers with very good results. Future research aims to create a complete system BCI that offers useful information to a specialist.

One of the major limitations in the development of the emotional and affective analysis is the lack of benchmarks to generate experimental results; the whole acquisition process had to be carried out in order to acquire data for analyzing and processing. This general problem that there is a wide range of data can be made difficult comparative work with the majority of researchers, because although the database IAPs and AIDS database used to build a reference database recordings EEG however, for the experiment conditions and materials registers implemented to acquire cause a variance between an investigator and others.

The application of these first steps helps provide a computational solution, although much more work needs to be development, but the possibility of implementing a way to measure the level of mental load or stress by analyzing brain signals holds promise because this analysis demonstrates that it is indeed possible to calculate distances behavior in electromagnetic signals with digital signal processing only.

The possibility of analyzing the emotional state of high performance athletes and provide useful information beyond the classical techniques, generates a diagnostic tool that can support the clinical study in the form of a computer system that is capable to provide real-time information, which is the main motivation for this project, as a strategy to support and monitoring.

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