Emotions Detection based on a Single-electrode EEG Device

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Abstract: The study of emotions using multiple channels of EEG represents a widespread practice in the field of research related to brain computer interfaces (Brain Computer Interfaces). To date, few studies have been reported in the literature with a reduced number of channels, which when used in the detection of emotions present results that are less accurate than the rest. To detect emotions using an EEG channel and the data obtained is useful for classifying emotions with an accuracy comparable to studies in which there is a high number of channels, is of particular interest in this research framework. This article uses the Neurosky Maindwave device; which has a single electrode to acquire the EEG signal, Matlab software and IBM SPSS Modeler; which process and classify the signals respectively. The accuracy obtained in the detection of emotions in relation to the economic resources of the hardware dedicated to the acquisition of EEG signal is remarkable.

1 INTRODUCTION

There are two main theories about the nature of emotions. One of them posits the existence of a relatively low number of basic emotions (families of emotions) that are universal for all human beings (Ekman et al., 1987; Levenson, 2011). At least six families have been proposed: happiness, sadness, repulsion, anger, fear and surprise. The dimensional theory, on the other hand, considers that emotions are represented in an N-dimensional space, where two of the coordinate axes would explain most of the emotional variations. These axes are called Valence and Arousal (Russell and Barrett, 1999). Valence is related to pleasure and varies from negative values (very unpleasant) to positive values (very pleasant). Arousal is related to the intensity of emotion, ranging from very low to very high. The two theories of emotions are not contradictory to each other. In fact the six basic emotions can be characterized according to their valence and arousal.

The theory of basic emotions includes, in turn, a locationist model that assumes that each emotional category starts from a specific place of the brain and body. Specifically, fear is located in the amygdala; the feeling of repulsion, in the insula; anger in the orbitofrontal cortex (OFC) and sadness in the anterior cortex of the cingulate (ACC) (Vytal and Hamann, 2010). Dimensional theory is included within the so-called constructionist model where it is asserted that emotions are psychological events that emerge from basic physiological operations, which are not specific to emotions. In (Lindquist et al., 2012) the authors propose a model with four components: core affect, a body sensory input that is experienced as pleasant / unpleasant (valence) with some degree of excitation; conceptualization, which links the body sensations with previous experiences to endow them with meaning; emotional words, used as support of emotional categories that are not clearly differentiable from the sensitive point of view; and executive attention, which focuses on some of the incoming stimuli. Some neuroimaging results have corroborated that, unlike what the locationist model predicts, any region that was activated during a basic emotion, was also activated for at least one other emotion (Lindquist et al., 2012). This suggests the existence of neural networks that interact with each other to generate the emotions, instead of precise places (locationist model). For example the amygdala is recruited for both fear and repulsion, so it takes different functionalities depending on the neural network that uses it.

There is no one theory that dominates, taking into account the results of neuroimaging, which can be interpreted differently according to the procedure used for the treatment of the data. (Hamann, 2012) summarizes the existing controversy pointing out that in the future, the analysis of animal models and studies on patients with brain injuries should be undertaken, which have been reported as tending more towards a locationist theory.

Emotions can be determined in several ways: through the analysis of gestures (facial or other), texts, speech (Liu et al., 2011), as well as the activity of various physiological variables. The electroencephalogram (EEG) is one of these variables. In this article we analyze the EEG and make use of the two-dimensional model.

There are a large number of devices with which EEG activity can be measured. These vary in price and how the measurement obtained is transmitted (wired or wireless). The use of a wireless device was opted for due to the advantages in mobility and adaptability it offers. Some devices that are on the market with these characteristics are: Emotiv (emo,), Neurosky Mindwave (emo,) and Enobio(eno,). Emotiv offers better results than the Neurosky Mindwave if it is used for the evaluation of cognitive processes (Das et al., 2014). Instead of the support offered, usability and its price so competitive is selected to make this study the Neurosky Mindwave. This has been widely used by the scientific community for the development of various applications such as the detection of sleepiness (Van Hal et al., 2014), level of attention (Liu et al., 2013), stress (Crowley et al., 2010; Maki et al., 2012), and so on. It is a device that offers developers and researchers the possibility to treat the measured signal, but it also comes integrated with a system that processes and delivers characteristics of the post-processing to the user, which will not be used in our case.

For the study and comprehension of the EEG signal, the analysis of the bands is widely used. Another feature used to study the EEG signal is the fractal dimension (Wang and Sourina, 2013; Siamaknejad et al., 2014) (in this study the Higuchi algorithm was used (Cervantes-De la Torre et al., 2013)). A fractal dimension close to 2 indicates that the signal is very complex, however a value close to 1 means that the signal is close to a line.

This study aims to analyze the characteristics of EEG signal, study the statistical behavior and make a classification of the emotional states using a set of images.

2 METHODOLOGY

2.1 Materials

To acquire the EEG signal we used Neurosky Mindwave. This device has an electrode placed at Fp1, according to the standard 10-20 system, and a fixed sampling frequency of 512Hz with a bluetooth interface. The data is read, saved and processed using Matlab 8.4.0.150421 (R2014b). To study the signal features we used the IBM SPSS Modeler, this software is a set of tools of data mining that allows for the quick development of predictive models, which offers a wide variety of modeling methods from automated learning, artificial intelligence and statistics (Corporation, 2012).

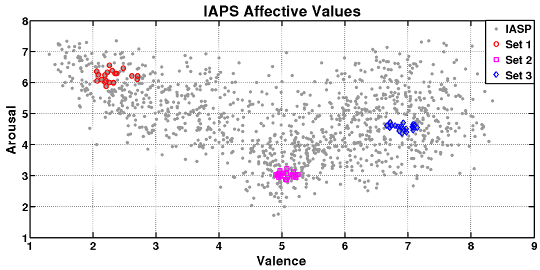

Figure 1: Valence and arousal values of the selected pictures.

2.2 Experimentation

Seven people took part in the experiment. Their average age was 29.85 with a standard deviation of 8.97. The experiment consists of displaying 60 pictures of the IAPS (International Affective Picture System), formed by three different groups of valence and arousal pairs (Figure 1), The first group has 2.306 $\pm$ 0.43 valence and 6.1890 $\pm$ 0.04 arousal, the second 5.063 $\pm$0.24 valence and 3,020 $\pm$ 0.02 arousal, while the third 6,921 $\pm$ 0.032 valence and 4,551 0.02 arousal.

Figure 2 depicts the timeline of the experiment. Before starting it, the SAM test was applied (*Self-assessment manikin*). This test allows a quick self-assessment of each participant indicating their initial values of valence and arousal. Then, the sixty IAPS pictures were shown randomly, each displayed for 6s, following the same procedure as in (Aftanas et al., 2001). Between each picture a resting picture with a black background and a gray cross in the center was shown for 4s (Hosseini and Naghibi-Sistani, 2011). This time lag between IAPS pictures reduces the overlapping effect on the EEG signal.

A Matlab software was developed to show the pictures, record the EEG data sent by Neurosky and introduce time marks to build EEG epochs associated with each IAPS picture and resting period. All the sessions were recorded by a WebCam to contrast any possible anomaly in the signal. Finally, participants completed a new SAM test for each picture.

2.3 Signal Processing

The EEG signal was segmented using windows of 512 samples (1-s) with a hop size of 64 samples (overlapping 87.5 %). A procedure has been developed for the automatic analysis of each epoch, in order to identify whether it contains a valid EEG signal, or whether it is contaminated by any type of artifact. These artifacts may have different sources: blinks, winks, eye movements, motion artifact, or muscle activity (EMG). In our case, the main source of artifacts have an ocular origin, because of the position of the electrode, although what is also important is the electrical activity of the frontal and temporal muscles and the artifacts due to the movement of the electrode.

The pre-processing of the signal looks to identify possible artifacts in each epoch. To accomplish this, we have used two features: the difference between the maximum and minimum sample value (MinMax), and the total energy (ESF) of the signal after applying a Savitzky-Golay lowpass filter (order 2 and length 35) (Schafer, 2011). Figure 3 shows the feature space. Epochs containing muscular activity have values of the MinMax feature that are similar or a bit higher than those of the epochs with only EEG, but with more energy from the filtered signal (ESF). Blinking or EEG-only windows have similar values in the ESF feature but differ in MinMax. Finally, windows with *motion artifact* contain values of these features that surround those obtained by other types of artifacts. For all these reasons, the use of thresholds (maximum and minimum) of each dimension of the feature space has been proposed, to limit and facilitate the automatic detection of valid EEG container segments and blinks (as shown in Figure 3) with an accuracy of 96 % and 98 % respectively. The method followed is conservative in the selection of valid epochs, reducing the number of false positives at the cost of increasing false negatives.

While motion and EMG artifact are infrequent, the ocular ones are not. There are techniques for removing ocular artifacts from the EEG signal. It is known that ocular artifacts influence, fundamentally, the lowest energy bands (δ, θ and part of α) so their non-elimination of analysis windows could distort the results. One of the most used techniques for elimination of these artifacts is based on the analysis of independent components (Stone, 2004), but, for their applica-

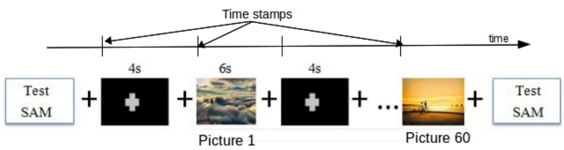

Figure 2: Experimental sequence.

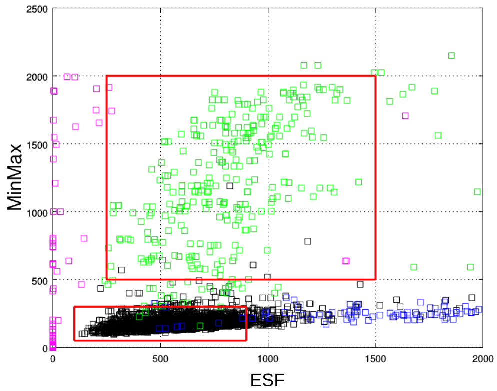

Figure 3: Feature spaces values for motion artifacts (pink), muscular activity (blue), blinks (green) and EEG (black). The selected areas to identify EEG and EEG+blinks epochs are also shown.

tion, at least two EEG channels are required, which do not exist in our case. However, in (Szibbo et al., 2012) a technique has been developed to eliminate such artifacts in a single channel. It is based on applying a low pass filter of the Savitzky-Golay type, with the same characteristics as the one used for the calculation of the ESF feature. Therefore, if an epoch is identified as a blinking container, this type of filter is applied before proceeding to the study in frequency.

The epochs containing no artifacts or only blinks which have been previously removed are then windowed with a Hamming function to reduce spectral leakage. Then the squared fast Fourier transform (FFT) is applied to each segment to obtained the typical energy bands:δ, θ, α and β. The fractal dimension is also calculated, so a total of 5 values per epoch were obtained.

2.4 Analysis

The averages of energy bands and fractal dimension of the epochs contained in every 6s of picture were obtained. From those averages the relation θ/β and θ/α was also included in the posterior analysis. This gives a total of 3x 20 x 7 numerical values for each set of images, picture and subject. Then we apply two different types of analysis: statistical and classification. The first looked for significant differences for each feature among the 3 sets of pictures. The second analysis sought to identify the accuracy in the detection of each set using a classifier based on a decision tree.

Table 1: Averaged values of each feature, subject and set of pictures. Values are $\times 10^7$.

Subject	Set1							Set2							Set3						
	δ	θ	α	β	$\frac{\theta}{\beta}$	$\frac{\theta}{\alpha}$	hfd	δ	θ	α	β	$\frac{\theta}{\beta}$	$\frac{\theta}{\alpha}$	hfd	δ	θ	α	β	$\frac{\theta}{\beta}$	$\frac{\theta}{\alpha}$	hfd
1	6,04	5,12	2,3	3,21	1,59	2,22	1,58	3,36	3,65	1,95	3,08	1,18	1,86	1,59	4,02	3,98	1,96	2,89	1,37	2,02	1,58
2	2,06	2,49	2,63	3,9	0,63	0,94	1,66	2,1	2,59	2,95	4,08	0,63	0,87	1,65	2,19	3,26	2,85	3,77	0,86	1,14	1,65
3	4,32	5,48	4,37	8,64	0,63	1,25	**1,57***	4,58	5,83	4,98	8,61	0,67	1,17	**1,55***	4,06	5,63	4,67	8,3	0,67	1,2	**1,58***
4	2,96	3,29	1,77	5,34	0,61	1,85	1,64	2,15	1,91	1,1	5,11	0,37	1,73	1,64	2,45	2,2	1,29	5,14	0,42	1,69	1,65
5	2,18	2,64	**1,56***	3,81	0,69	1,69	1,68	1,61	2,09	**1,1***	3,51	0,59	1,88	1,68	2,29	2,88	**1,47***	3,6	0,8	1,95	1,67
6	4,68	4,94	3,09	4,5	1,09	1,6	**1,58***	4,54	4,64	3,09	4,73	0,98	1,5	**1,6***	3,56	4,4	3,05	4,76	0,92	1,44	**1,63***
7	1,11	1,24	**0,69***	4,51	0,27	1,78	**1,71***	2,62	1,9	**1,32***	4,53	0,41	1,43	**1,68***	2,13	2,53	**1,64***	5,07	0,49	1,53	**1,69***

2.4.1 Study 1

The mathematical tool used to perform the first analysis was ANOVA (Analysis of Variance) applied to each person and to the seven features ordered by set of images, in order to check if, at least one of the sets of images, is significantly different from the rest.

2.4.2 Study 2

The second analysis was performed using the classification algorithm C 5.0, which generates a decision tree. The division of the samples was based on the node that offers the maximum gain of information in each level and allows several divisions in more than two subgroups iteratively until it arrives to perform Divisions that do not have a significant impact on the model, which are discarded. The 7 features are taken as input data for each image and have three nominal values (the three sets in which the images have been grouped). Then for each person the accuracy of the correspondence established between each image and its respective group is calculated. This is done using IBM SPSS Modeler software, with the option of partitioning the data, to ensure that they have not used the same information as in the model generation.

3 RESULTS

Table 1 shows the absolute values of the features obtained for Study 1, grouped according to a sub-set of images and a subject. The values that have been shown to be statistically significant, with a value of $p < 0.5$, are emboldened. Subjects 3, 6 and 7 obtained values significant for the fractal dimension and subjects 5 and 7 in the α band. However, there is not a clear relationship between features' behavior and changes on valence and arousal. For example, for subject 3, the fractal dimension has a behavior concave with the sub-set of images (from set1 to set3). However, for the subject 6, the same feature, has a growing monotone behavior. Subject 7 has a concave behavior too although between Set2 and the Set3 there are no changes in the fractal dimension.

Subjects 5 and 7 show significant changes in the α band. However, like with the fractal dimension, there is not a regular pattern of behavior of this feature when we vary the sub-set of images. For example, while subject 7 shows a behavior growing monotone in the α band (from Set1 towards Set3), subject 5, has a concave behavior.

In Table 2 the results of classification by subject can be seen, which are around 81% accurate.

Table 2: Accuracy in detecting emotional states.

Subject	Accuracy
1	78,33%
2	78,33%
3	76,67%
4	73,33%
5	91,67%
6	81.67%
7	85%
Mean	**80.71%**

4 DISCUSSION

To facilitate the understanding of the results, the *Arousal* and *Valence* results according to IAPS (Figure 1) and the most significant features (hfd and α), depending on the groups of selected images, are shown (See figures 4 and 5).

4.1 Significant Features Analysis

The fractal dimension is related to the complexity of the EEG signal, which is increased in neural activation processes. In (Colibazzi et al., 2010) an experiment was carried out with neuroimaging to find out which areas of the brain are activated by know visual stimuli categorized with different values of valence and arousal. It is suggested that a stimulus with positive valence decreases activity in the right hemisphere, mainly in r-dLPFC and AMCC areas. In contrast, for a stimulus with positive excitement, activity in the left hemisphere present a growing monotony, fundamentally in thalamus and amygdala. Since the measurement system mainly picks up the activity that is located in the left hemisphere, the signal must be

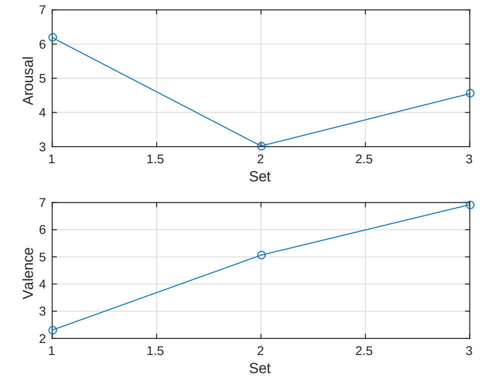

Figure 4: Valence and Arousal variation of the three set of selected pictures.

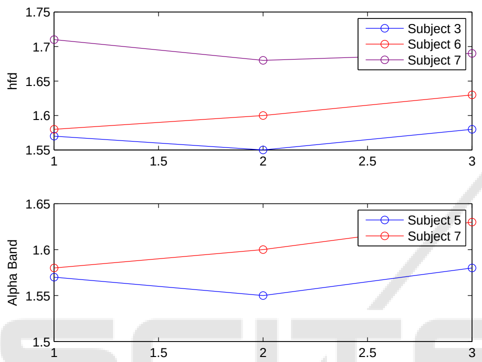

Figure 5: Variation of the two statistically significant features for each set and subject.

more influenced by the arousal than by the valence. Moving from set1 to set2 it is shown a decrease in arousal and an increase in valence is shown, but the fractal dimension for subjects 3 and 7 decreases as a consequence of that reduction of activity in the left hemisphere. When passing from set2 to set3, both valence and arousal increase, growing the fractal dimension, as occurs with subjects 3, 6 and 7.

Another neuroimaging study (Nielen et al.,) determines that the zones that are activated during changes of valence and arousal differ from the previous one, but which also justify, to some extent, the changes obtained in the fractal dimension. In it, the arousal increase is correlated with the activity's increase in the areas associated with the medium temporal gyrus (mT) and vLPFC. The behavior of valence is more complex, as for negative values of this there is a reverse neuronal activity with valence in the LPFC and direct with it for positive values in the orbitofrontal and mT regions. All activation areas can influence the signal sensed with greater or lesser weight. In any case, the change from set1 to set2 causes a generalized decrease of the prefrontal and temporal activity that could justify the decrease of the fractal dimension. The step from set2 to set3 shows increase of activity in orbito-frontal (valence) and mT (valence and arousal). There may be some compensation in the measured signal as a function of the valence, as both the sensor Fp1, affected by the orbitofrontal zone, such as reference (located near the temporal lobe) could counteract its effect, leaving only the dependence of the arousal on the reference sensor, and, therefore, in the recorded signal. This could justify the increase of the fractal dimension.

The behavior of the other feature, the α band, does not correspond to any valid fact in the revised scientific literature. For example, an EEG system with 19 electrodes was used in (Valenza et al., 2015) to analyze the influence of valence and arousal on power bands. The authors used pictures of IAPS classified according to two classes of valence (positive and negative) and four levels of arousal. It was concluded that there were significant changes in the bands θ and β in the PFC and the parietal zone for intermediate values of arousal. In (Aftanas et al., 2001), using 62 electrodes, they found significant differences in the band θ in the anterior temporal zone. There are effects of lateralization, since for negative valences, it was observed a greater synchronization (activation) in the left hemisphere, whereas for positive valences, the same effect was observed in the opposite hemisphere.

4.2 Classification Results

In (Yoon et al., 2013) a method was proposed to identify four emotional states: active, commitment, pleasure and neutral using the same system as in this paper, but instead of being based on the pure signal, it is based on two parameters: levels of mediation and attention. The achieved classification accuracy was 66% with data from 42 participants. In (Brown et al., 2011) the percentage of classification was 82%, higher than that obtained in this last work, but based on the use of 9 electrodes, located mainly in the prefrontal area and in both hemispheres and based on the ratio of the α band between the sensors located in symmetrical positions between both hemispheres. In (Chanel et al., 2007) 9 bands distributed between [4, 20] Hz were used as features for training two classifiers (LDA -Linear Discriminant Analysis- and SVM -Support Vector Machine-) and three classes (excitated, little excited, neutral) for arousal and two classes for valence (positive, negative). The best results were obtained with SVM with 67% for arousal and 76% for valence. In (Liu et al., 2011; Sourina and Liu, 2011) , the fractal dimension was used to classify states of excitation and valence with three electrodes.

One of them, located at FC6, was used for the arousal and the difference between the AF3-F4 electrodes, for the valence. Using three states for each variable (positive, neutral and negative) they achieved an accuracy ranging from 70% up to 100% in some cases. In (Bos et al., 2006) power bands were used as features for the classifier and a reduced number of electrodes. In particular, for arousal it was observed that the best classification result, 97.4 was with β band between the electrodes F3 / F4, while that for valence, the result was of the 92.3% in the same F3/F4 or in Fpz.

4.3 Affective Assessment

Finally, figure 6 shows the averages of reported arousal and valence for each set of pictures per subject (circle) and the averages for all subjects (*).

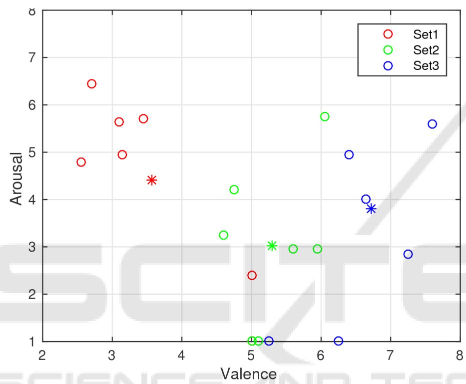

Figure 6: Mean experimental valence and arousal values for each set of pictures and subject.

Although it can be seen that averages per subject approximate to the values of the IAPS (except for set1, whose valence is greater and the arousal is lower), the dispersion of the values reported for each of the 20 pictures is quite higher than those indicated in the IAPS database. These variations could be due to cultural factors. In a study carried out in Spain with more than 800 people, an adaptation of the values of valence and excitation of the IAPS have been proposed (Moltó et al., 1999). The results differ slightly from values reported in the IAPS, but, in the case of this work, the dispersion obtained for each set was even larger than the collection made by the Spanish adaptation. This could justify, in large part, why significant v ariations a mong t he m easured f eatures for the different sets of pictures have not been obtained.

5 CONCLUSIONS

The study shows the way in which an EEG channel is used and can perceive the response of neuronal activity to stimuli; in our case, visual stimuli.The validity of using a low-cost commercial device such as Neurosky MindWave for the acquisition of the signal is checked. After implementing a classification algorithm, emotions are detected with an average accuracy of 81% of total stimuli.This value exceeds the results obtained in most of the studies reported in the literature, either for those who use a reduced number of channels of EEG or for those who make the measurement with a considerable number of electrodes.

There seems to be a direct correlation between the signal complexity and the arousal; on the contrary, having a single electrode does not have sufficient information to give any conclusions about the valence.There are variations between the IAPS data and those reported by the people in the SAM test applied at the end of the experiment. It could influence in the correspondence between the features expected, taking as reference the IAPS and those experienced by the subjects.

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