# Analysis of the Emotions' Brainwaves

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***Abstract*—Currently in Peru, patients with degenerative diseases, such as Amyotrophic Lateral Sclerosis (ALS) have lost of communication ability. Many researchers' papers that establish basic communication system for these patients. It is also essential to know their feelings or state of mind through their emotions, in this study, we present an analysis of electroencephalographic signals (EEG) applied to emotions such as fear, tenderness, happiness and surprised; it was used linear discriminant analysis (LDA) to get the identification and classification of the 4 emotions with a success rate of 63.36% on average.**

***Keywords—Electroencephalogram; EEG; emotions; amyotrophic lateral sclerosis; degenerative diseases; classification learner***

## I. Introduction

Approximately 210 cases of ALS of which more than 50 are located in Lima, more cases in people aged 30 to 59 years. It should be mentioned that the total cases of degenerative diseases are approximately 5% of the national population, of which a significant part has already lost their motor and communication capacity. In this sense, it has been working in many applications and EEG studies such as: [1], [2], [3], [4] in which systems are created in order to support patients suffering from degenerative diseases, however it is also essential to study the emotions in this type of patients, in order to achieve improvements in communication as we can understand their emotions and feelings.

In the present work, the classification of emotions is carried out, [5] which are intense affective events that arise in the face of the perception of transcendental situations for a person. Emotions are states in which a combination of sensations and feelings determines the behavior of people; we will focus on studying fear, tenderness, happiness, and surprise. Since, they are essential to be able to know the primary emotional state of the patient.

Fear is the emotion that communicates that the person is in danger; with this, we can know the potential danger in which the patient or the people that surround them can be.

Happiness is produced as a result of something favorable, that likes or benefits; we could identify if the patient is comfortable with the care provided.

The surprise guides us in unexpected situations; thanks to this emotion, we can identify that the patient could be in an uncomfortable situation.

The tenderness reflects the affection, love for a person or animal or thing, with this emotion, the patient will be able to express his affection towards his loved ones as well as the people that surround him.

In [6] they analyzed the emotions sadness, anger and surprise, mention that there are investigations that show that there is a link between the frontal lobe of the brain and emotions, finding that positive emotions are shown on the left and negative ones on the right.

In [7] they decompose the signals generated by emotions into ten sub-bands and use neural networks with a Feedforward Backpropagation algorithm to achieve the classification of the signals.

In [8] propose a method of spectral asymmetric index (SASI), for data divided into 5 bands, in positions fp1 and fp2, in order to detect emotions in the beta (13 - 25Hz) and theta (4 - 8 Hz) frequencies also use a gradient boosting decision tree (GBDT) algorithm for the classification of positive and negative signals.

In [9] they show that the most active area of the brain, concerning emotions is the right side, they achieved it by observing the power of the alpha band (8 - 12 Hz), for the condition of disgust in the temporal regions, front and back.

In [10] they worked with emotions happiness, sadness, angry and relaxed. Dividing the signals into the gamma, beta, alpha, and theta bands, demonstrating the beta and gamma bands are reliable bands for recognizing emotion with the EEG signals; further mentioning that the alpha band can also be considered for the recognition of emotions while theta band can be ignored.

In [11] they study happy, calm, sadness and frightening emotions, showing that the alpha and beta bands contain useful characteristics, also mentions that when a subject sees emotional stimuli, the power decreases in the alpha band but increases in the beta band, In other words, the distribution of the power spectrum in the brainwave patterns changes.

Section II presents the methodology that has been followed for the research work. In Section III, the reader will find the preliminary results obtained. Section IV shows the respective discussions and conclusions for this research work.

## II. Methodology

For the present work, the method to follow is outlined in the block diagram shown in Fig. 1.

### A. *Acquisition of Data*

For the data acquisition stage, the OpenBCI system has been used, [12] which consists of the main board that is the Cyton Board, which is an Open Source tool, used for the acquisition of EMG, EEG and ECG signals; together with its complement (Daisy Board), they have 16 channels, from which data can be obtained at a sampling frequency of 125Hz. The OpenBCI system communicates wirelessly via Bluetooth to the computer through OpenBCI Dongle (Programmable USB).

For the reception of data, the pc uses Python, as a bridge for the transmission of data via Lab Streaming Layer, then the data is received in Matlab, with the use of a graphical interface which is in charge of collecting the data and save them in text files (Fig. 2).

The EEG signals are obtained through the 16 channels of the OpenBCI system, which corresponds to the positions Fp1, Fp2, C3, C4, T5, T6, O1, O2, F7, F8, F3, F4, T3, T4, P3, P4, of the international system 10/20 (Fig. 3).

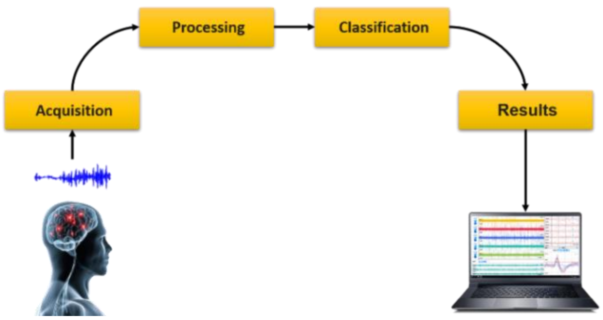


Fig. 1. Work Scheme.

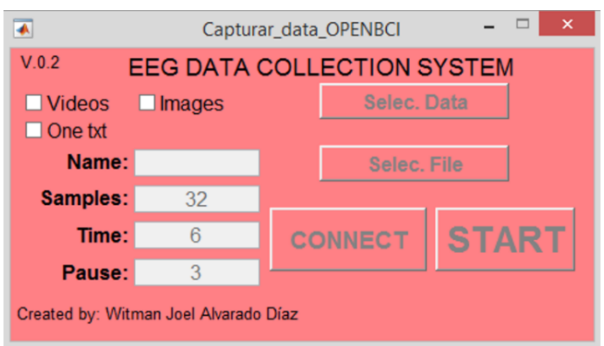


Fig. 2. System for Data Acquisition.

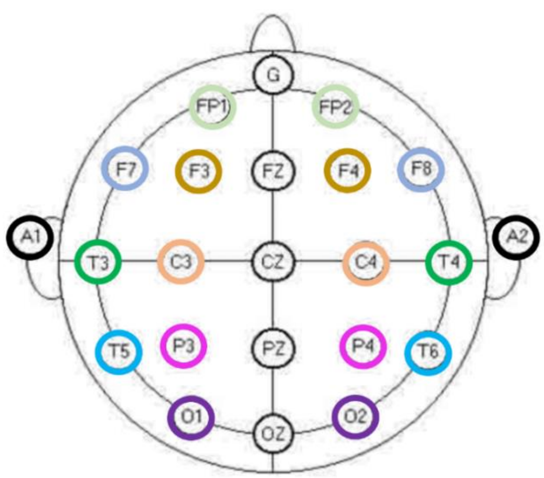


Fig. 3. Positioning of Electrodes According to the 10/20 System.

## B. Processing and Classification

As part of the data processing, we write a code in Matlab which links the data, in Fig. 4, the reader can see the flow chart which we describe below.

First, we request the entry of the name of the data, and create a directory then the following steps are followed:

- We read the first file and delete column 17th since it only contains data of the time elapsed during the acquisition of data.
- We create a vector with the class to which the data belongs.
- Next, we enter a loop that is responsible for reading the files one by one and joins them to the first file mentioned above; also, it does the same for the classes to which the data belongs.
- Finally, the whole matrix is transformed into a table of 192 x 7501 in which the last column corresponds to the classes.

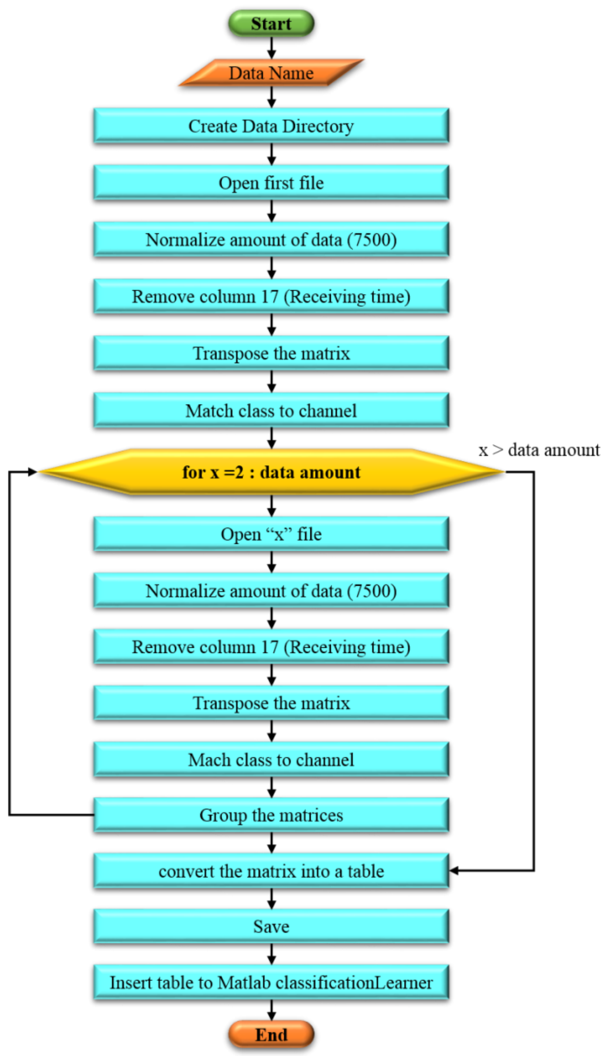


Fig. 4. Flow Chart for Grouping the Data.

## III. Results

Samples were taken to five people, to which they are shown 3 videos for each emotion of 1 minute each, for the feelings, surprise, happiness, tenderness and fear as the reader can see in Fig. 5, the 12 videos are shown in a way randomly, and also the collected data is saved in different files.

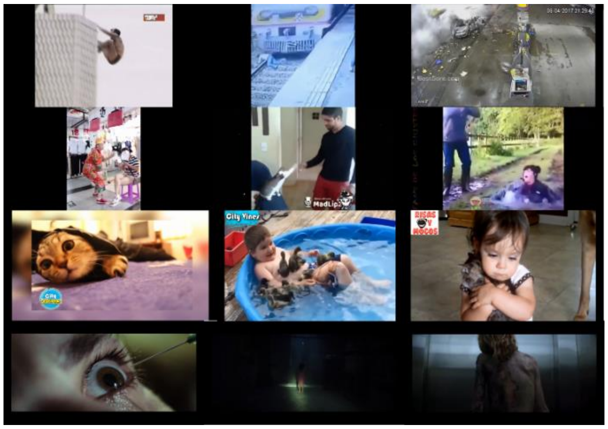

Fig. 5. Captures of the Videos Shown During Data Acquisition.

As mentioned above, the Matlab Classification Learner application was used to classify the data into four different classes corresponding to each emotion studied, using linear discriminant analysis (LDA) with a full covariance structure and five cross-validation cuts.

The linear discriminant analysis (LDA) also known as Fisher's linear discriminant, named for its inventor Sir RA Fisher; this analysis has been applied for decades, according to [13] and [14], the LDA has a statistical approach to reduce the dimensionality of the data, calculating an optimal projection, in order to minimize the distance within the classes and maximize the distance between classes. The classical LDA requires that the total dispersion matrix will not be singular however according to [14] and [15] in many problems such as information retrieval, facial recognition, machine learning, bioinformatics, data analysis, etc.; the total dispersion matrix mention previously can be singular, since the dimensional data is usually very high and the dimensions generally exceed the number of data points generating a sampling problem or singularity.

In [15], [16], [17], [18] many mathematical formulas and LDA algorithms are described, it is mention for example that the LDA can be used to classify an X observation of a q-dimensional vector which it obtains by observing one of several classes that may be unknown; one of the several ways to describe the LDA is through the use of probability models; assuming that the class $i$th has a density $f_i(X)$ and a probability $\pi_i$, taking into account Bayes formula, which tells.

$$P(class = i|X) = \frac{f_i(X)\pi_i}{\sum_j f_i(X)\pi_j} \quad (1)$$

To demonstrate the Bayes rule or classifier, which says that the largest conditional probability classification will obtain the least expected number of errors, it assumes that class $i$ has a Gaussian distribution with mean $\mu i$ and covariance $\sum$ , it is demonstrating that classifying the maximum conditional probability is equivalent to classifying

$$\arg\ max_i\,(L_i) \quad (2)$$

Where $L_i$ is the discriminate function.

$$L_i = X^T \sum{}^{-1} \mu i - \mu_i^T \sum{}^{-1} \mu_i/2 + \log(\pi_i) \quad (3)$$

When using the maximum similarity estimates for $\mu i$ take into account that $L_i$ is a linear function of X since it goes at the LDA procedure.

The LDA is a fast and accurate algorithm, which assumes that the different classes generate data based on Gaussian distributions; in the MATLAB tool, the LDA uses the "fitcdiscr" (Fit discriminant analysis classifier) function, which returns a discriminant analysis model or a classifier, based on the input variables contained in a table and the output, responses or labels.

When the application started and later adding the data already prepared, we can see its graph Fig. 6; then we choose the analysis that we want to do and start the application.

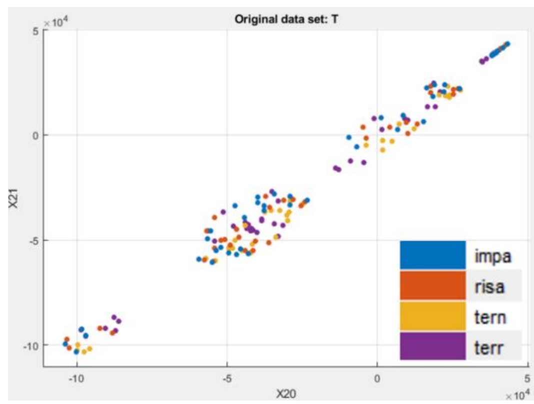


Fig. 6. Data Plotted by the Classification Learner Application.

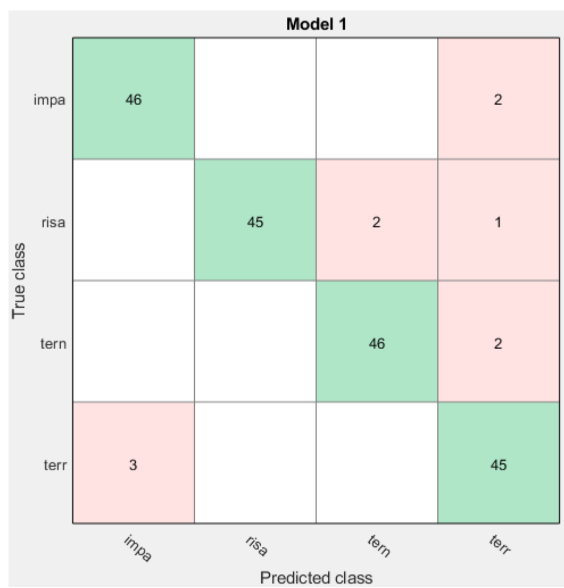


Fig. 7. Confusion Matrix Generated by the Classification Learner Application.

As a result, the application performs the classification of the data and provides us with a confusion matrix Fig. 7 in which we can see the performance of the chosen algorithm.

Having in mind that the data entered into the application have only been linked, so it is "unprocessed" with which efficiency of 63.36% is obtained on average in Table I, we can see respective efficiencies for each test subject.

TABLE I. TABLE OF ACCURACY

| Name Data | Accuracy (%) |
|---|---|
| Subject-1 | 31.8 |
| Subject-2 | 67.2 |
| Subject-3 | 94.8 |
| Subject-4 | 43.8 |
| Subject-5 | 79.2 |

## IV. DISCUSSION AND CONCLUSIONS

For the classification of emotions, different algorithms can be used as in the works [19], [8]; we obtain better results with linear discriminant analysis, and the use of the Classification Learner application.

In work [20] they obtained 55.3% applying linear discriminant analysis studying the emotions anger, fear, and surprise, evoking the emotions through videos.

Also in the consultation [6], they obtained an efficiency between 48.78% and 57.04% using the linear discriminant analysis and support vector machine, working only in the identification of positive and negative emotions, in the right and left part of the frontal lobe.

Finally, in [10] an efficiency of 91.01% is obtained, in the study of happiness, sadness, anger and relaxed, it was achieved by decomposing their data in the signals corresponding to the frequency bands of the brain.

As we can see in other works, it has been possible to classify the brain signals produced by emotions; in our case, a preliminary efficiency of 63.36% was obtained on average.

For future work, we will take into account the accuracy obtained to process the data and perform the analysis on more people, which will allow us to improve the methodology and achieve better results.

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