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VISIÓN ELECTRÓNICA

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VISIÓN ELECTRÓNICA

Psychophysiological Analysis of Sound Stimuli

Análisis Psicofisiológico de Estímulos Sonoros

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Abstract

Electroencephalography signals (EEG) has captured the general interest of the scientific community; nowadays, the most part of the investigations of the topic are focused on the emotional psychophysiological effect that this kind of signals are able to show according different types of stimuli; therefore, this document shows the analysis of different sets of EEG signals, captured by NeuroSky headset, under the stimulation produced by emotional content sounds from the IADS (International Affective Digital Sounds); furthermore, some EEG signals from the "DREAMER" dataset were also analyzed. From this document was mainly concluded that there was a corresponsive result between subjective and objective data as valence and

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arousal values were corresponsive with EEG frequency bands; furthermore, for DREAMER set, electrodes of the right hemisphere were the ones with more energy.

Keywords: EEG, Neurosky, IADS, Digital Signal Processing, DREAMER.

Resumen

Las señales de electroencefalografía (EEG) han captado el interés de la comunidad científica; actualmente, la mayoría de las investigaciones están enfocadas a cómo estas señales reflejan la respuesta psicofisiológica de las personas, en términos emocionales, respecto a diferentes estímulos; por esta razón, en este documento se presenta el análisis de señales de EEG captadas por el headset de NeuroSky ante estímulos sonoros con contenido emocional provenientes de la IADS (International Affective Digital Sounds); además, se analizaron algunas señales del dataset de EEG "DREAMER". De este desarrollo se llegó a que hay una correspondencia entre los valores de Valencia y Arousal con las bandas de frecuencia de EEG, observando además que, para el caso del DREAMER, los electrodos correspondientes al hemisferio derecho presentaban la mayoría de la energía en el cerebro.

Palabras clave: EEG, NeuroSky, IADS, Procesamiento Digital de Señales, DREAMER.

1. Introduction

1.1 EEG-assisted emotion recognition: A state-of-the-art review

Tables 1-3 list the types of EEGs available on the market, as well as their cost and number of electrodes:

Table 1. Commercial EEG equipment [1].

Product tier	Products	Channel positions	Sampling rate	Electrodes	Cost
Low-cost range (USD99-USD 1,000)	Emotiv EPOC+	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	32 Hz–64 Hz	14	USD 799.00
	NeuroSky MindWave	FP1	512 Hz	1	USD 99.00
	Ultracortex "Mark IV" EEG headset	FP2, FP1, C4, C3, P8, P7, O2, O1	128 Hz	8–16	USD 349.99
	Interaxon Muse	AF7, AF8, TP9, TP10	256 Hz	4	USD 250.00
Middle-cost range (USD 1,000-USD 25,000)	B-Alert X Series	Fz, F3, F4, Cz, C3, C4, P3, P4, Poz	256 Hz	10	(Undisclosed)
	ANT-Neuro eego rt	AF7, AF3, AF4, AF8, F5, F1, F2, F6, FT7, FC3, FCZ, FC4, FT8, C5, C1, C2, C6, TP7, CP3, CPz, CP4, TP8, P5, P1, P2, P6, PO7, PO5, PO3, PO4, PO6, PO8	2048 Hz	64	(Undisclosed)

However, according to [1], optimal readings are not necessarily obtained from the more expensive EEGs. Similarly, the installation on the scalp is easier because of the number and type of electrodes, requiring a more precise installation at the time of implementing the EEG on a test subject. The same article classifies and defines in Table 2, the main frequency bands in which the brains can be found under certain conditions, bands extractable from the various EEG systems presented above.

Table 2. EEG signals and frequency bands [1].

Band	Frequency band [Hz].	Functions
Delta	< 4	Associated with the unconscious mind and occurs in deep sleep.
Theta	4 - 7	Associated with the subconscious mind and occurs during sleep.
Alpha	8 - 15	Associated with a state of mental relaxation and correlated with brain activation.
Beta	16 - 31	Associated with an active mental state and occurs during a focused mental activity
Gamma	>32	Associated with intense brain activity

Below, in Table 3, the authors of [1] present some commercial EEGs with their corresponding electrode positions and the frequency bands that can be captured with these devices.

Table 3. EEG equipment with their corresponding frequency bands [1].

EEG helmet	Electrode location description	Frequency bands captured
BioSemi ActiveTwo	Prefrontal, prefrontal-frontal, frontal, frontal-central, temporal, central, central-parietal, parietal-occipital, occipital	Theta, Alpha, beta-low, beta-high, beta-high, gamma
NeuroSky MindWave	Prefrontal	Delta, theta, Alpha-low, Alpha-high, beta-low, beta-, beta-high, gamma-low, gamma-medium
actiChamp	Frontal, central, parietal, occipital	Delta, theta, Alpha, beta, gamma
AgCl electrode hull	-	Delta, theta, Alpha, beta, gamma
BioSemi ActiveTwo	Frontal, Prefrontal, prefrontal-frontal, frontal, frontal-central, temporal, central, central-parietal, parietal-occipital, occipital, occipital	Delta, theta, Alpha, beta, gamma
BioSemi ActiveTwo	Prefrontal, prefrontal-frontal, frontal, frontal-central, temporal, central, central-parietal, parietal-occipital, occipital	Delta, theta, Alpha, beta, gamma
Emotiv EPOC+	Prefrontal-frontal, frontal, frontal-central, temporal, parietal, occipital, frontal-central	Delta, theta, Alpha, beta, gamma
Muse	Temporal-parietal, prefrontal-frontal	Delta, theta, Alpha, beta, gamma
NeuroSky MindWave	Prefrontal	Delta, theta, Alpha, beta, gamma
Emotiv EPOC+	Prefrontal-frontal, frontal, frontal-central, temporal, parietal, occipital, frontal-central	Delta, theta, Alpha, beta, gamma
BioSemi ActiveTwo	Prefrontal, prefrontal-frontal, frontal, frontal-central, temporal, central, central-parietal, parietal-occipital, occipital, occipital	Delta, theta, Alpha, beta, gamma

IADS is a standardized database of digital sounds used to evoke emotional responses, applied in research where the emotion and attention of individuals are studied. In addition, [1] mentions an experiment that consisted of capturing the EEG signal of 4 IADS stimuli, with a duration of 60 seconds, in order to classify the emotions evoked in the test subjects. DREAMER, on the other hand, is a collection of EEG signals obtained by exposing 23 participants to audiovisual stimuli; this is a complement to the present EEG signal analysis project.

Finally, in the state of the art, it is also mentioned here that EEG physiological readings can be obtained in a practical way since its implementation does not involve inserting the patient in any machine, generating claustrophobia; in addition, there is no need for interaction between the subject and the machine. At an emotional level, EEG is used in medicine to diagnose and characterize mental disorders, being a reliable tool to collect and store data for later analysis by a specialist [1].

1.2. Psychophysiological responses of young people to soundscapes.

This study analyzes the psychophysiological effect of various soundscapes on university students in two (2) different configurations, one with the natural soundscape and the other adding punctual elements to that soundscape [2].

From this article, it is important to point out that as a psychological response a subjective scale proposed by the authors is used, while for the physiological response they use different mechanisms such as heart rate, blood pressure and EEG capture with the recording device: NeuroSky. From this development, it is important to note that the brain activity index β/α was used, explaining that this index, among others, is the most suitable to show a marked physiological response to different stimuli. In this article, the brain activity index is described as an indicator of liking with respect to the soundscapes used. From the study, it can be concluded that nature sounds are more pleasant and relaxing compared to everyday sounds, which are more annoying to people [2].

1.3. ASCERTAIN: Emotion and personality recognition using commercial sensors

ASCERTAIN is a database that correlates emotions with physiological measures obtained through various devices, such as EEG, resulting in nonlinear relationships that are suitable for understanding the correlation between emotion and physiological response. This was verified by analyzing the EEG signal from a NeuroSky device, extracting from the collected data the average of the first derivative, the proportion of negative differential samples, the average number of peaks and the average derivative of the inverse channel signal. For some of these statistics, NeuroSky also has specialized software for this task.

1.4. DREAMER: A data-base for EEG-based emotion recognition

This study deals with the development of an EEG and ECG database, matching these values with audiovisual stimuli for different emotional contents [4]. For the development of this database, the EMOTIV EPOCH helmet with 14 electrodes was used.

Figure 1. EMOTIV Epoch hull for generating the DREAMER database (a) Hull, (b) Electrodes and nomenclature in the database [4].

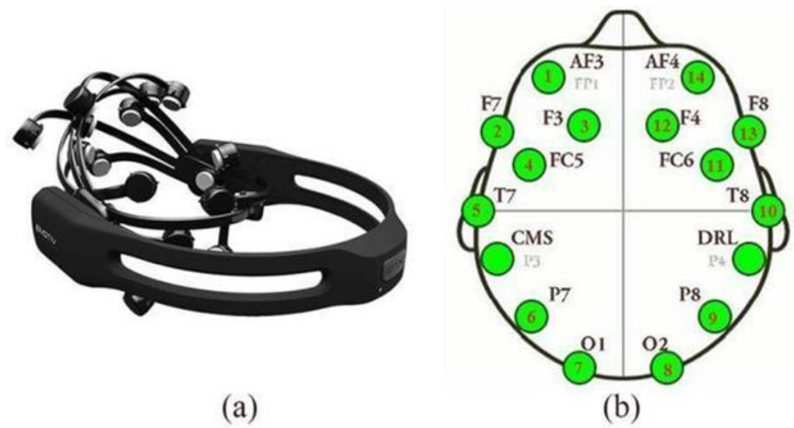
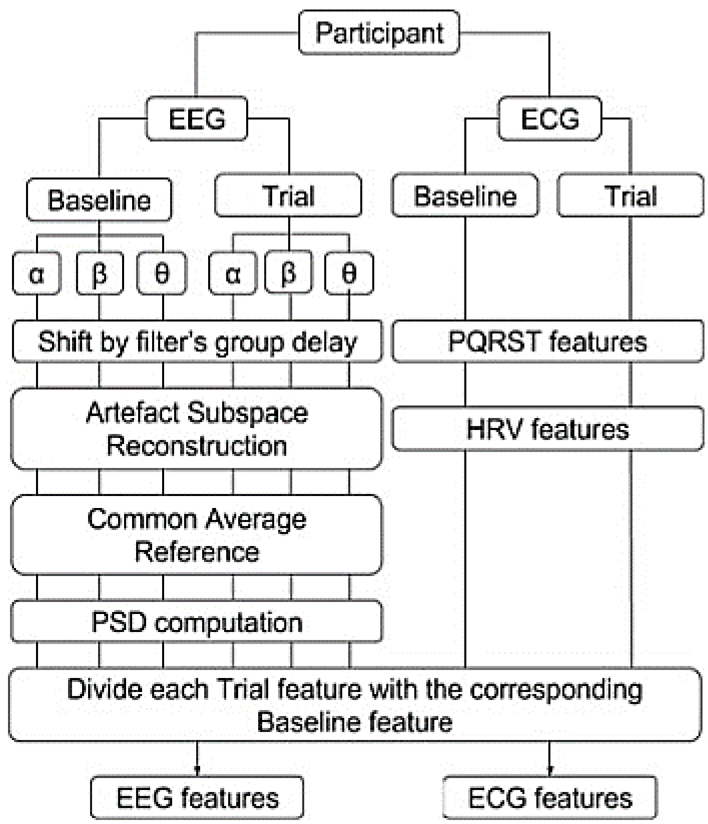


Figure 1.b. shows the positioning of the electrodes used with their corresponding nomenclature in the data set. From this study, it should be noted that, for data processing, we used a normalization of the data captured from the stimuli with respect to a baseline captured immediately before the stimulus. This operation allows the removal of residual activity existing before the stimulus was taken. In this sense, the data are measured with respect to a reference [4]. It should be noted that only the Theta, Alpha and Beta frequency bands are analyzed through their spectral density indices.

The data from this database were used to develop an emotion identification algorithm based on SVM (Support Vector Machine), taking as a reference the subjective responses submitted by the users. Figure 2 shows a diagram of the data processing performed on this dataset, where the normalization with respect to the baseline can be seen.

Figure 2. Data Processing [4] for the DREAMER database



1.5. Real Time Emotion Recognition System with EEG

This paper discusses some methods for obtaining emotional variables in EEG-captured data, with the following methodology:

Figure 3. Data processing used by [5].

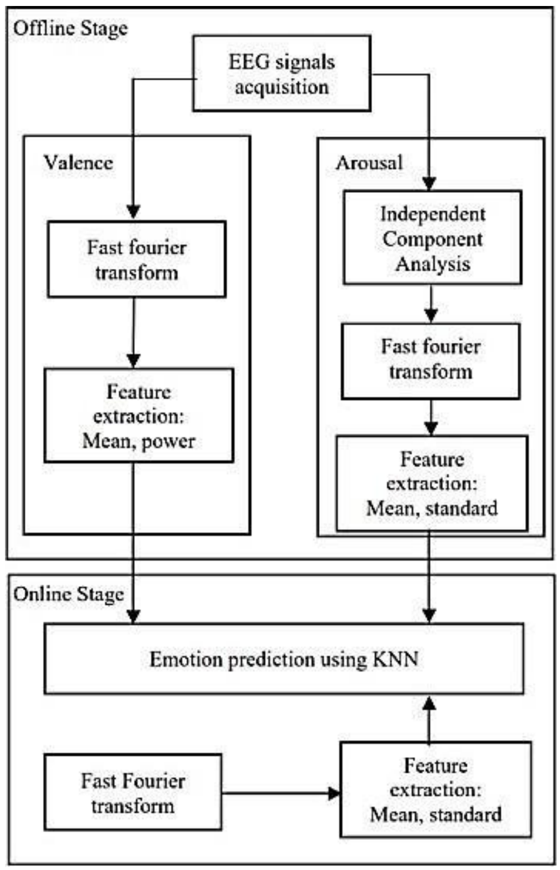


Figure 3 shows the steps to have an emotion prediction model, which acquires EEG data as input values, and then performs two processes: in the case of Valencia, an FFT is applied to extract from the temporal signal converted into frequency, the main measurements (mean and power) for then perform the KNN model of emotion prediction. For the case of data with Arousal, an ICA procedure must be performed to determine the location of those electrodes that were affected by the brain stimuli, and the subsequent steps are performed similarly to the case explained above.

The KNN model, by using artificial intelligence, needs some input values to be able to perform the prediction model, therefore, it is necessary to introduce EEG signals to which FFT is performed to extract the main measures previously seen.

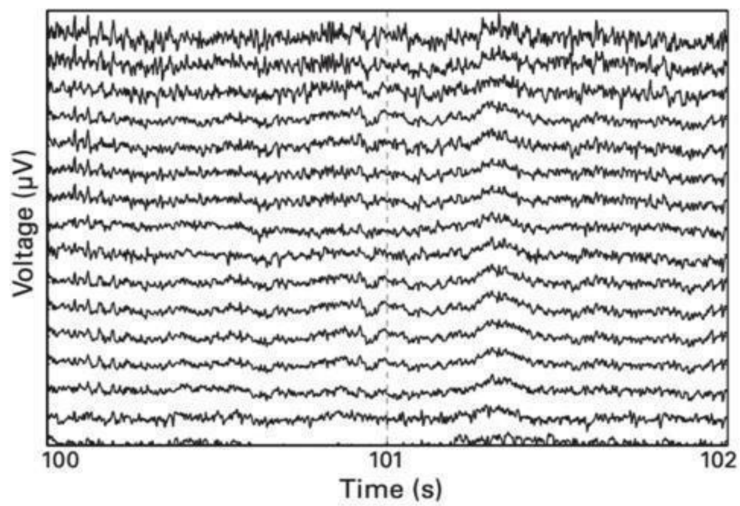
2. Theoretical basis

2.1. Electroencephalography (EEG)

It is a test that allows measuring the voltages produced by the electrical activity of neurons in the brain; this with the help of an amplifier and at least two electrodes, a passive reference electrode and an active measurement electrode, which allow quantifying the potential difference between these two. The electroencephalogram, or EEG, was discovered by Hans Berger, today known as the father of EEG, during World War II when he demonstrated the electrical potential of the brain through an amplifying device he called electroencephalograph, a device without the need to have the skull exposed to electrical measurements as Richard Caton previously had to do with other mammals [6].

These signals obtained from the electroencephalogram, being normally very sensitive devices, are affected by involuntary movements of the people undergoing the tests, as occurs with the blinking of the eyes, in addition, as the electrical activity of the brain is measured, thoughts and what is known as imagination can influence the voltage variations captured by the EEG, for example, just thinking that you are moving your arm without actually moving it will have an effect on the raw EEG signals (raw EEG data), which correspond only to the voltage variations of the measurement electrode with respect to the reference electrode [7]. Figure 4 shows an example of what the raw EEG signals look like when obtained from multiple electrodes, and each line in the graph is an electrode in the example presented.

Figure 4. Raw EEG data for several electrodes [8].



Raw EEG data signals tend to vary greatly (as seen in Figure 4) and have obvious artifacts for the reasons explained above; therefore, time-varying EEG signal cleaning filters are often applied with respect to the parasitic frequencies (present at low frequencies between 0 and 2 Hz, as well as at high frequencies between 30 and 60 Hz depending on the device used). use); In addition, cleaning algorithms called Independent Component Analysis (ICA) are usually applied, which perform source separation, involving a decomposition of the raw EEG data into a set of components that will allow the identification of artifacts or independent sources of the data. variation [8]; This type of algorithm is usually applied when there is a considerable number of electrodes that allow an adequate decomposition of the source.

2.2. EEG frequency bands

Because time-varying EEG data are affected by artifacts and have small and highly variable voltage values, EEG-based studies generally perform frequency-domain analyses, determining oscillatory patterns of electrical fluctuations occurring between neurons in the brain. These tend to be more stable than the temporal information provided by raw EEG data signals and provide information about the amount of electrical energy provided by the brain in a given pattern (or, rather, frequency) of oscillation. These oscillation patterns are usually of low frequency (1 to 40

Hz), where each range denotes a different physiological state with respect to the brain electrical activity that the subject has. Table No. 2 shows the different brain waves with their respective frequency limits according to [1]; However, in the case of this article, the brain wave limits are considered according to [4], since, as some of the signals presented in the DREAMER dataset are intended to be analyzed, it is considered appropriate to adapt the same frequency. limits used for this study. In the following, in Table No. 4 presents the frequency limits of each brain wave along with their interpretation in the literature.

Table 4. Frequency ranges of brainwaves and corresponding mental states [6].

Type of brain wave	Frequency range	State of mind
Theta	4 - 8 Hz	Creativity, fantasy, imagination, dream, unconsciousness
Alpha	8 - 13 Hz	Relaxation, calm, imagination; between unconsciousness and consciousness
Beta	13 - 20 Hz	Awareness, focus, agitation moderate

2.3. PSD Spectral Power Density

The Power Spectral Density (PSD) present in a signal indicates the distribution of the signal power distributed in each frequency band present in the signal, thus being able to establish the bands in which the greatest amount of signal power is concentrated. This is practical when analyzing such behavior in frequency since it is possible to easily discriminate the frequency intervals than if a time domain analysis of the signal were performed. The PSD is mathematically defined as:

$$S_{NX}(w) = \frac{1}{N} \left| X(e^{jw} \right|^2 \quad (1)$$

Where $S_{NX}\,(w)$ is the signal for which we want to perform the PSD in the frequency domain and N is the number of frequency intervals to be considered [9]. To calculate the Spectral Potential Density with the help of Matlab one should use the command "bandpower" which is a proprietary function to which the input signal (x) is entered and returns the power average (p); by the following command: "p= bandpower(x)". If the input signal (x) is a matrix, then the function "bandpower" will return the average power in each column independently [10].

2.4. Brain activity index Q/a

This is an indicator that expresses brain activity according to the spectral density indexes of the Beta and Alpha bands. This index has been used in different studies as a parameter to quantify the physiological response of the brain in comparison with other indexes of brain activity that are related to the theta band; example of these studies is [4] and [11]. This index is calculated with equation (2) shown below:

$$\frac{\beta}{\alpha} = \frac{\beta_{spectrum} - \alpha_{spectrum}}{\alpha_{spectrum}} \quad (2)$$

Where $\beta_{spectrum}$ and $\alpha_{spectrum}$ correspond to the PSD calculated for the frequency ranges of these brainwaves [11].

Regarding this index, it is said that a higher value is consistent with liking and commitment, while lower values are related to irritation and fear; from another perspective, when compared to activation levels, it is said to be proportional to Arousal, i.e., higher values of Arousal indicate more activation.

2.5. Filter Design

Filters in digital environments refer to a mathematical operation, to which a series of numbers is entered (in), and this generates another series of numbers (out) defined as the characteristic transfer function of the filter, with the objective to highlight or attenuate a certain region of the signal, in this case, digital. There are several types of filters, which can be implemented for specific cases within the signal processing, for the purposes of this project the Butterworth type filter is required, since it presents a flat response to the cut-off frequency, ideal for filtering EEG signals without affecting too much those regions that you want to leave intact.

This operation can be performed with the help of Matlab, using the command "y = filter(b,a,x)", which calls a function with "b" and "a", which are the coefficients of the number and denominator respectively of the transfer function, "x" which is the signal to be filtered and delivers the filtered signal "y".

3. Methodology

This section shows how the acquisition process was carried out, for which 3 test subjects were chosen. As a first step, the EEG equipment (Neurosky) was installed and the participants were subsequently instructed that the measurement would be performed with their eyes closed, as shown in Figure 5.

Figure 5. Collection of experimental data

Next, EEG information is collected for 30 seconds without stimulus and immediately after playing the IADS stimulus for 2 minutes, then the test subject is allowed to rest for approximately 1 minute and then re-recorded for another 30 seconds. of silence and then the test subject was subjected to another IADS stimulus. Thus successively until all previously chosen IADS stimuli were censored, following the methodology presented in [4].

Among the data collected experimentally with the help of the IADS and NeuroSky stimuli versus the DREAMER database.

As for the data collection for DREAMER, which is only in females, the stimuli were extracted from one with responses to these stimuli related to the project. To process both the data acquired by NeuroSky and those extracted from DREAMER, it was decided to create a code that extracted the PSD for each brain band of analysis (Theta, Alpha and Beta) for both the stimulus and the baseline. These data were recorded in several tables shown in the results section below. As for the In general terms, the code only consists of loading the EEG data, selecting the analysis electrodes in the case of the DREMAER, and for the information of each electrode, several filterings are performed on the signal so that the signal is found within the frequency ranges corresponding to each frequency band. With this, the data are computed with the MatLab band power function, entering the filtered signal for each case, the frequency limits for analysis and the sampling frequency (128 Hz).

In addition, in the case of DREAMER, the EEGLAB suite was used to extract the PSD graph of all the electrodes to observe the difference in energy captured by each electrode used. It should be said that AF3, AF4, O1, O2, T7 and T8 are chosen; the first two to see the general activity that the brains have in the prefrontal lobe, the occipital lobes for the activity related to vision and the temporal for the auditory activity.

Finally, the data are stored for subject/stimulus, calculating β/α with equation (2).

4. Results and analysis

After performing the procedures explained in the previous section, the following results were obtained. In the case of NeuroSky, the PSD of each brain frequency band was compared between each subject together with their valence and excitation data. The results are shown in Table 4.

Table 4. Results for NeuroSky

NeuroSky	Theta	Alpha	Beta	Beta/Alpha	Valencia	Arousal
HVHA						
Sujeto 1	1,2	1,1	1,1	1,1	7	4
Sujeto 2	1,5	1,1	0,9	1,1	9	7
Sujeto 3	2,7	9,1	5,1	1,9	7	4
LVHA						
Sujeto 1	1,5	1,6	1,1	1,5	4	8
Sujeto 2	0,7	1,0	1,2	0,8	2	9
Sujeto 3	0,9	1,2	1,5	0,5	5	8
NVNA						
Sujeto 1	3,3	2,6	3,0	0,9	6	6
Sujeto 2	0,4	0,3	0,4	0,6	5	5
Sujeto 3	0,8	1,1	1,4	0,6	5	5

From these data it can be seen that there is a correspondence between the EEG data and the subjective valence and arousal scores when these scores are compared with the PSD of each brain frequency band; Slight differences are observed between each subject, which may be due to the fact that, as indicated by several studies involving the comparison between subjective and physiological tests, the test subjects may be biased as to what they think they feel in front of the stimuli, while with physiological tests we have the scoop that "the body does not lie", having a more adequate approximation to what the person feels in front of the stimuli.

Observing the subjective test scores, there is a correspondence between the emotion that each stimulus was intended to produce, since all subjects gave scores that belonged to the category of valence and arousal that the original sound stimuli had, being HVHA high in valence and arousal. The LVHA is low in valence and high in excitation and the NVNA is neutral in valence and excitation, so it is correct to state that the sound stimuli produce, taking into account the subjective test, the emotions that were expected to be obtained.

On the other hand, when comparing the PSD between subjects, it is easy to identify which stimulus activated each subject more. In the case of the first subject, it is observed that he was more influenced by the NVNA stimulus, evidencing greater energy in the theta band, which may indicate that this stimulus, having valence and excitation values that are close to a neutral and calm state, the subject enters a state of creativity and almost unconsciousness with respect to what he hears; this is argued and complemented with valence and arousal information, where, for the subject in question, the stimulus is pleasurable and calm. Something similar happens with the second subject, except that this happened with the HVHb stimulus, which may indicate that, for this subject, happy stimuli can induce creativity and reverie. Regarding the last subject, a greater influence of the HVHA stimulus was observed, presenting greater energy in the Alpha frequency band; This is interesting since it has a high correspondence with the valence and Arousal values given by the subject, where a happy and calm stimulus is evident; having more energy in Alpha than in the others, it is valid to say that the subject felt calm and relaxed, in a point between the conscious and the unconscious, which is also evident in the Arousal score where, for this subject, the stimulus tends to be relaxing in terms of arousal.

Table No. 5. Results obtained for DREAMER

Sujeto 1						
DREAMER	Theta	Alpha	Beta	Beta/Alpha	Valencia	Arousal
Estímulo 1 (Calma)						
AF3	1,0	1,5	1,4	1,4	8	4
AF4	1,0	1,5	1,5	1,2		
T7	1,1	1,7	1,6	1,3		
T8	1,1	1,4	1,2	-5,3		
O1	1,0	1,4	1,3	4,5		
O2	1,1	1,5	1,4	2,0		
Estímulo 2 (Miedo)						
AF3	0,9	0,8	0,7	0,9	2	8
AF4	1,2	0,8	0,5	0,4		
T7	0,5	0,8	0,8	0,9		
T8	0,5	0,8	0,7	0,8		
O1	0,5	0,9	0,8	3,4		
O2	0,7	1,0	0,9	2,6		
Estímulo 3 (Felicidad)						
AF3	0,8	0,8	1,0	3,6	8	8
AF4	0,8	0,8	1,0	3,0		
T7	0,4	1,0	1,4	1,6		
T8	0,5	0,8	1,3	2,2		
O1	0,5	0,7	1,0	7,5		
O2	0,4	0,6	1,1	3,4		

Briefly, Table 5 shows that, at a general level, stimulus No. 1, which is related to calmness, is the one with more energy in the Alpha and Beta frequency bands.

This was to be expected since they reflect the emotional characteristic that surrounds this stimulus.

With respect to the second stimulus, it is observed that β/α has lower values in comparison with other stimuli, a fact that correlates with the pleasantness that the person feels with respect to the stimulus, obtaining a higher value for the third stimulus corresponding to happiness.

With respect to the third stimulus, the Beta frequency band has higher energy than the others for this stimulus; this is in agreement with the theory of this frequency band designating a state of alertness, agitation and concentration, aspects of the stimulus analyzed.

For these data it was also appropriate to obtain the PSD plots for the 14 electrodes considered, so that it could be observed in which parts of the brain the highest energy is observed; this is shown in Fig. 6. From here it is possible to observe the variation of each stimulus at the spectral level of the signal, noting that the fear stimulus (stimulus 2) has more abrupt peaks and greater presence of energy in the high-frequency bands.

From these graphs it can also be seen that most of the energy is concentrated at electrodes 14, 13, 10, 8 and 1, which according to Fig. 1 of the nomenclature of each electrode for the data set, would be electrodes AF4, F8 , T8, O2 and AF3 respectively; This allows us to evidence that most of the energy in all three cases is concentrated in the right hemisphere, which is logical considering that it is the hemisphere that is mainly responsible for vision and hearing; Furthermore, with respect to electrodes T8 and O2, in addition to AF3 and AF4, they are the ones with the highest energy, which corresponds to the fact that in the case of the former it may be related to the auditory cortex of the brain, while the latter is related to the visual; re checking the influence of the audiovisual stimuli used.

5. Conclusions

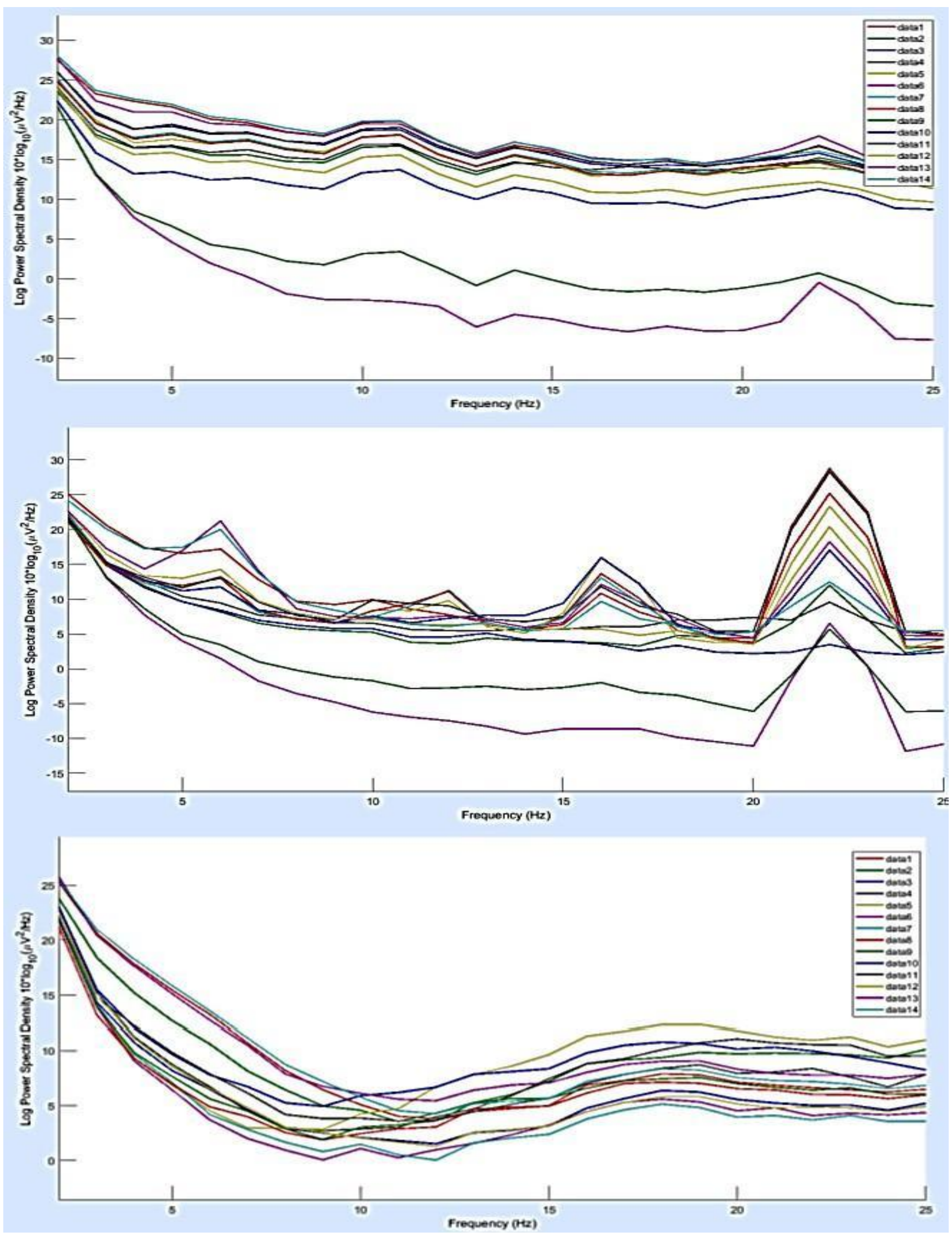
The treatment of EEG signals in the frequency domain presents a more intuitive way of analyzing what happens to the signal in the frequency intervals; this procedure is performed by applying an FFT to the EEG signal obtained from the device.

EEG represents a practical and economical solution for the measurement of physiological stimuli, however, the processing of the signals obtained for analysis can become cumbersome depending on the manufacturer.

Correspondence was found between the valence and arousal values with the values of each of the frequency bands; where the β/α index reflects the variation of the person's liking in the physiological aspect in most cases, while the individual Beta and Alpha bands denote the amount of activation with respect to the presented stimulus.

Higher energy was observed in the right hemisphere for the DREAMER data, presenting higher energy in electrodes AF3, AF4, T8 and O2 corresponding to the visual and auditory part of the brain, reflecting the influence of the audiovisual stimuli used, Figure 6.

Figure 6. PSD plots for each electrode of the subjects analyzed with DREAMER**.** From top to bottom: Calm stimulus, fear stimulus, happiness stimulus.



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