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Design of an EEG analytical methodology for the analysis and interpretation of cerebral connectivity signals

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Abstract

The objective of this study is to design an Electroencephalographic (EEG) analytic methodology that allows to develop a variety of analysis and interpretations of brain signals. The initial phase considers the acquisition and filtering of EEG signals, the division into bands in data ranges, and the storage of EEG signals in a cloud data base. Then, an analytical phase considering descriptive, predictive and prescriptive analysis is accomplished. A sequence of analytic intermediate processing steps is done in order to render a graphic visualization of significant correlations between pairs of EEG channels. Pearson correlation is utilized to detect synchronic connectivity through the brain areas. Time series in nearly instantaneous time lapses are treated by using Hilbert Huang Transform. An experimental design by submitting a set of students to an abbreviated version Raven visual test is made providing results in correlation maps of cerebral connectivity.

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Keywords: EEG Analytic Methodology; EEG Signal Analysis; Cerebral Connectivity

1. Introduction

The study of EEG signals usually obeys a certain objective, which means using specific analytical tools aimed at that objective. However, in an exploratory study, when the state variables involved are not totally clear, even despite the associated bibliography, it is convenient to count on some tools that provide an initial relationship among these variables, in order to guide the research, especially aimed at people who do not suffer from a disease.

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Some time ago, brain activity was supposed to depend on static and specific areas of the brain Brodman Areas [1]. However, applying graphic techniques nowadays is useful to determined that the relation within the EEG signal is not static, but that it obey behaves according to a systemic relation [9], [10].

In the domain of thermodynamics, the brain compensates for its deviations towards greater organization by generating heat as a by-product of its metabolism [7]. Each neuron must contribute its small share in the payment for ordering an open system (the brain) [8], situated in a universe whose overall tendency is towards disorganization and disorder.

2. EEG Signal Analytic Methodology

2.1. Phases of the Methodology

The study of an EEG signal can be divided into two main phases: a first phase of signal acquisition from an EEG sensor, filtering of artifacts presents in the signal, band division of the signal and storage in a cloud database. A second phase, considers a descriptive analysis classifying into different groups according to some specific criteria (similarity, measures, deep analysis), a predictive analysis and a prescriptive analysis and interpretation within each group, which allows to generate an analytics problem solving hypothesis and conclusions, as presented in Figure 1.

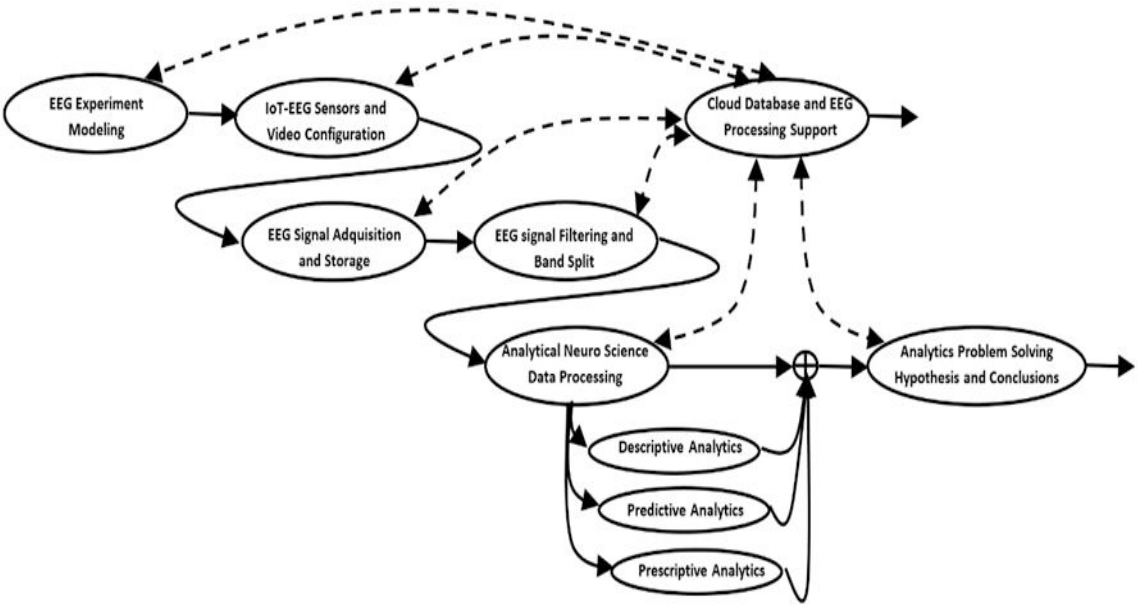


Figure 1. EEG Signal Analytic Diagram

2.2. EEG Signal Acquisition and Artifact filtering

Signal acquisition is composed of hardware and software which takes the scalp signal and transforms it into a digital signal with a sampling frequency of 128 or 256 Hz. The process involves a fast Fourier transform and a final exportation of data with the extension .edf (european data format). The brain-computer interface and the Emotiv Epoc® scientific contextual EEG are used in order to obtain the sequence of data coming from 14 positions of the scalp and, by extension, of the cerebral cortex, referring to the 10 / 20 standard EEG channel location system [2].

The second module corresponds to the EEGLAB Toolbox, an Open Source software that works with .edf,, .edf + extensions as well as other formats used in the sampling of EEG signals. The filters that are applied in EEGLAB are ADJUST filter; remove gross artifacts and perform ICA [3]. These filters are already programmed and their use can be chosen in combination. At this point, in order to approve the validity of the sample, the intervention of a user is essential due to the necessity to visually check the graphic of the EEG signals (Channel Data {Scroll}) in search of artifacts that the EEGLAB Toolbox is not able to recognize by itself.

Once the artifact filtering process is finished, in addition to generating the baseline, the signal can be grouped according to some classification criteria, to be analyzed later. One of the most common criteria is frequency band division [2].

2.3. EEG Signal Band Division

Although there is no unified criterion in this segmentation, it is mostly accepted that there are five bands, with their boundaries as detailed below:

(Delta) frequency]0,4[Hz.: Sleepy, dreaming.
(Theta) frequency [4,8[Hz.: Drowsy, meditative.
(Alpha) frequency [8,14[Hz.: Relaxed, reflective.
(Beta) frequency [14,30[Hz.: Alert, working
(Gamma) frequency [30, + [Hz.: Active thought.

Since the invention of the EEG, numerous investigations have studied the relationship between brain waves and different states of consciousness. It is known that different brain wave patterns are directly related to different states of consciousness, such as intense concentration, alertness (awake), deep sleep, vivid dreams, drowsiness, relaxation, hypnosis, altered states of consciousness, etc. In the case of this document, the interpretation in each group is to be performed within the frequency bands shown above. Figure 2 shows some of them [2].

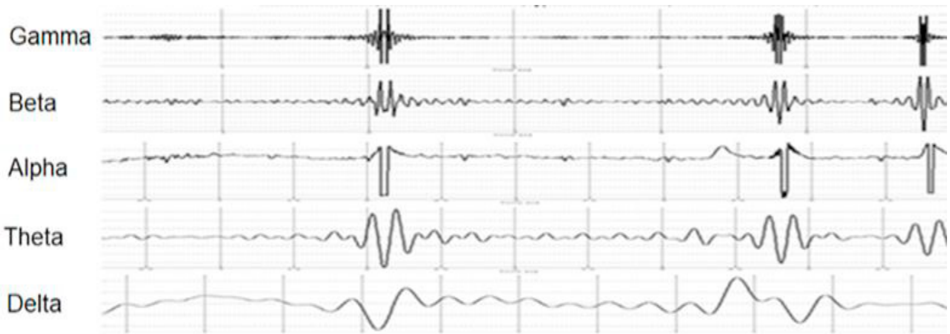


Figure 2. Frequency bands, including temporal domain and its amplitude (voltage)

2.4. Storing EEG signals in Cloud and ROLAP DB

A relational and multidimensional database have been implemented in a modality known as ROLAP, so that all interrogation actions on the multidimensional database are performed through queries that must be reinterpreted in the SQL language [4].

2.5. Similarity of signals per Frequency Bands

It is sought to determine the similarity of signals in a given lapse, assuming that the indicator is likely to be a Pearson correlation, with absolute value, greater than 0.8. Signal interpretation, focused on brain connectivity, works as follows. Under the assumption that, during a given lapse, specific areas of the brain are triggered simultaneously to perform an activity, the recorded signal (by the electrodes that capture it) must have a similar behavior. The sample statistic, to determine this relation R (x, y) is given by the following equation:

$$R(x,y) = \frac{n\ \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2}\ \sqrt{n \sum y_i^2 - (\sum y_i)^2}} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)\ s_x\ s_y} \tag{1}$$

Where xi and yi correspond to points in two compared signals, both at the moment i. On the other hand, n is the total time in the lapse studied.Once the correlation matrix is obtained for each sheet, the significant data for R (x, y) is summarized and plotted on an image that accounts for these values. The color black is used for values of R $\geqslant$ 0.8000 and red for R $\leqslant$ -0.8000. Figure 3 shows the arrangement of the EEG electrodes, on which the correlations are drawn [5].

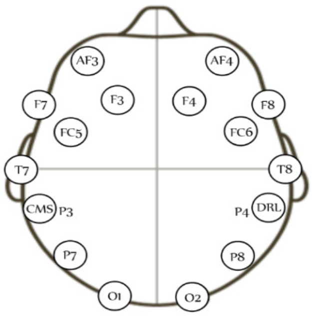


Figure 3. Electrode arrangement on the used electroencephalograph

2.6. Deep Analysis using Hilbert Huang Transform

When using Pearson correlation, the relationship established is between two series, in a given lapse. In this case, the time each student takes to respond to each Raven picture, in a signal broken down by frequency bands. Therefore, the tool measures an average value.

To investigate two times series in smaller (or even instantaneous) lapses, it is convenient to decompose the signals by Hilbert Huang transform. This adaptive heuristic is used especially with non-linear, non-stationary and non-periodic signals. It begins with the decomposition of an original signal not needing to establish an initial basis, as Wavelet or FFT (Fast Fourier Transform) do, but adapting to each signal (EMD, Empirical Mode Decomposition), so that the sum of decompositions is equal to the original signal. This avoids having to make any initial assumptions about the characteristics of the signals.

The product of this decomposition, called IMF (Intrinsic Mode Function) is analyzed as a Hilbert spectrum, which allows to analyze the instantaneous frequencies and amplitudes. Figure 4 shows a decomposition, in instantaneous frequency and amplitude of the IMF3 [6].

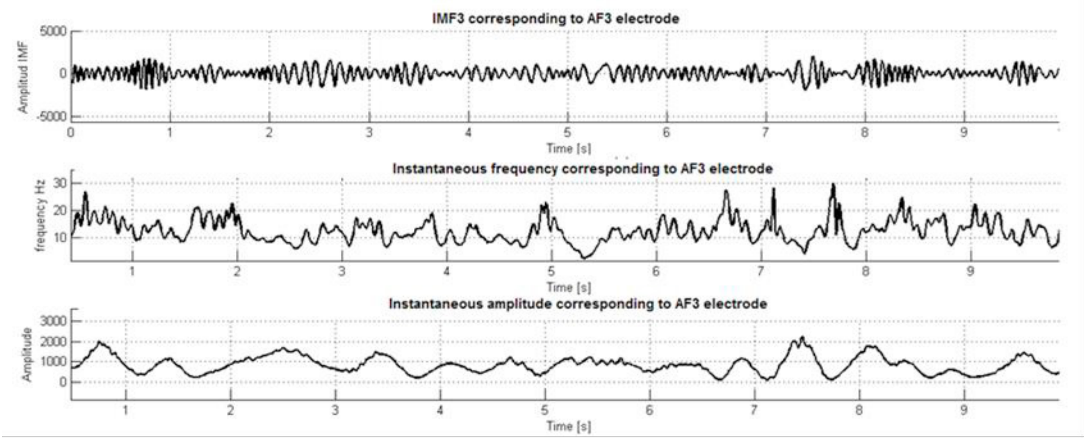


Figure 4. Decomposition of component 3 (IMF3) in instantaneous frequency and amplitude

3. Experimental Design

Brain Connectivity is to be examined, that is, the relationship between two signals in a time span, using Pearson correlation coefficient. A student is asked to solve a visual test in which they match a picture that is presented to them with a test picture, known as “Raven Progressive Matrices Test”, or “Raven's Progressive Test” (Raven's Progressive Matrices) [7]. An intelligence test was chosen because it is an accepted tool and is frequently used in the estimation of Intellectual Quotient (IQ). It has some key characteristics in relation to the experimentation that is pursued. Firstly, it is a generic test, that is to say, it is independent of the age, sex, language and culture of the individual. Secondly, it is a visual test and brain activity of the sense of sight can be found in a zone of the brain (occipital and temporal), therefore it can be recognized and analyzed in detail when processing the signals.

The sample intended is 20 students of different levels of industrial civil engineering and industrial execution engineering, males and females and aged between 18 and 26 years old [8]. The sampling is carried out in a suitable laboratory, it takes about 20 minutes for each student. During the Raven test, the computer screen where the test is being performed is captured, and then it is analysed how they respond and how long they may take.

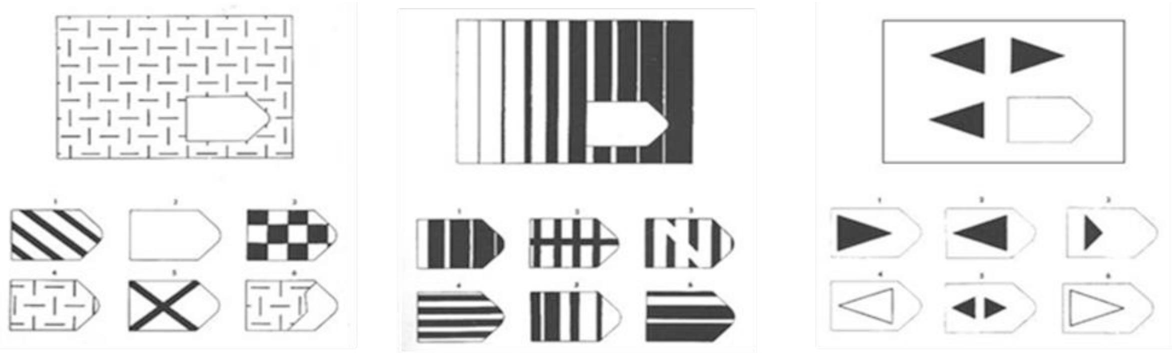


Figure 5. From left to right, questions 1, 9, 15 of the Raven's Progressive Matrices test. Cmplexity increases as the item number does.

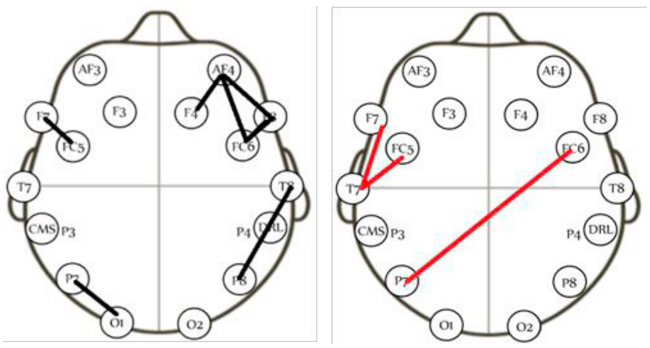
4. Results

Once the signals are obtained by each channel, they are grouped according to two criteria: first, according to the frequency band (delta, theta, alpha, beta, gamma) and according to the period that the student took to resolve each sheet. Table 1 shows the correlation matrix for a student in the solution of the first sheet (5.62 seconds) in the alpha band.

From this matrix, correlation values greater than or equal to R ⩾ 0.8000 are chosen. The assumption is that the value of the correlation (for the combined variation of two signals, in the lapse in which a student responds to each of the 15 sheets) is high enough to assume that they have a similar shape. On the contrary, if R ⩽ -0.8000 allows to assume that while one signal grows, the other decreases. Figure 6 summarizes this data in a table and is associated with an image.

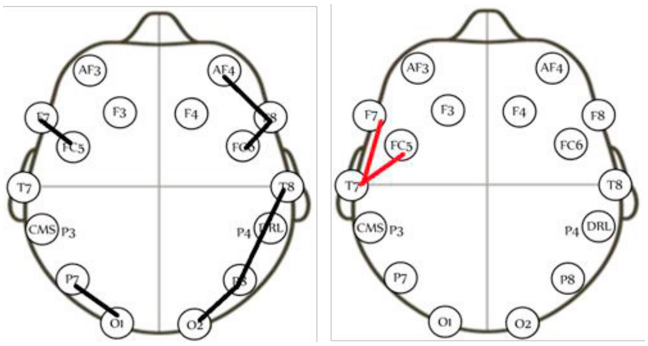
Table 1. Correlation matrix for sheet 1 of the Raven Test, in the alpha band (t = 5.62 seconds, at a sampling rate of 128 Hz)

	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
AF3	0,2249	0,3627	0,2236	-0,221	-0,323	-0,505	0,3444	0,6754	0,7028	0,5218	0,4472	0,7002	0,4411
F7		-0,036	0,9558	-0,827	-0,134	-0,373	-0,432	0,1112	0,3448	-0,141	-0,135	-0,374	-0,255
F3			-0,205	0,1463	-0,524	-0,557	-0,037	-0,097	0,0865	0,2124	0,5819	0,4083	0,3485
FC5				-0,886	-0,139	-0,374	-0,493	0,0669	0,3046	-0,055	-0,075	-0,344	-0,2
T7					0,4689	0,6374	0,5131	-0,131	-0,494	-0,305	-0,124	0,0646	-0,191
P7						0,9076	0,4682	0,0835	-0,31	-0,817	-0,55	-0,549	-0,665
O1							0,3675	-0,083	-0,512	-0,7	-0,706	-0,534	-0,698
O2								0,7431	0,4249	-0,06	0,0297	0,4215	0,2046
P8									0,8788	0,2949	0,0316	0,5259	0,3526
T8										0,5058	0,2932	0,5878	0,5887
FC6											0,4919	0,829	0,8029
F4												0,6565	0,7983
F8													0,8652



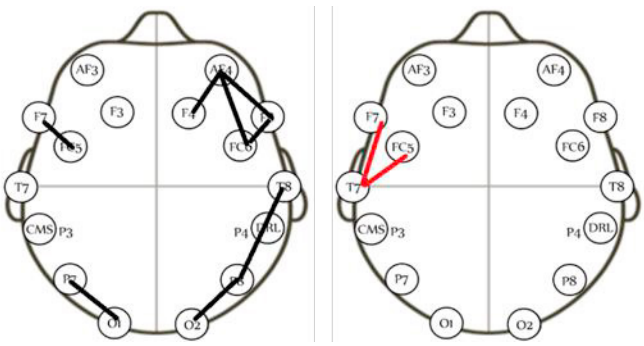
R ≥ 0,8000		R ≤ -0,8000	
FC5 - F7	0,9558	T7 - F7	-0,8269
O1 - P7	0,9076	T7 - FC5	-0,8861
T8 - P8	0,8788	FC6 - P7	-0,8171
F8 - FC6	0,829		
AF4 - FC6	0,8029		
AF4 - F4	0,7983		
AF4 - F8	0,8652		

Figure 6. Map and table of significant cross correlations of the Raven Test for sheet 1, in alpha frequency. In black, R ⩾ 0.8000; in red, R ⩽ -0.8000. The resolution time is 7.67 seconds.



R ≥ 0,8000		R ≤ -0,8000	
FC5 - F7	0,9082	T7 - F7	-0,8083
O1 - P7	0,8379	T7 - FC5	-0,8676
P8 - O2	0,7861		
T8 - P8	0,9056		
F8 - FC6	0,7971		
AF4 - F8	0,854		

Figure 7. Map and table of significant cross correlations of the Raven Test for sheet 9, in alpha frequency. In black, R ⩾ 0.8000; in red, R ⩽ -0.8000. The resolution time is 10.14 seconds.



R ≥ 0,8000		R ≤ -0,8000	
FC5 - F7	0,9214	T7 - F7	-0,7857
O1 - P7	0,9319	T7 - FC5	-0,8365
P8 - O2	0,8091		
T8 - P8	0,88		
F8 - FC6	0,8747		
AF4 - FC6	0,8132		
AF4 - F4	0,8059		
AF4 - F8	0,8419		

Figure 8. Positive and negative correlations for sheet 15 of the Raven test. Resolution time 15.09 seconds

As can be seen in Figures 6 to 8, regardless of the time taken by the test subject to respond to the three sheets shown, there are certain positive and negative correlation patterns that are maintained.

For R ⩾ 0.8000 (shown black in the figures), regardless of the difficulty of the item being resolved, the activated areas are almost the same. For this level of significance, it is inferred that, on average, during the lapse that the resolution of the item lasts, the corresponding electrodes capture a joint work (observing that the areas captured by the electrodes are acting synchronously, on average). Something similar happens with R ⩽ -0.8000, only that the interpretation would be "deactivation of one zone by another". A more important detail is simultaneously manifested: there are zones that act in both ways (those captured F7, FC5).

5. Conclusions

The proposed methodology of EEG signals analytics allows to model and develop a considerable variety of analyses and interpretations of brain signals. It is particularly used to identify patterns by descriptive-visual analysis based on Pearson correlation coefficient, and subsequently to support the basis of a prospective study, based on the Hilbert Huang transform.

In the case of the experimental analysis developed, the EEG signal is captured, filtered and segmented to generate a pattern identification procedure, within a set of dynamic data. In this phase, an average estimate of patterns within the data set is pursued, using Pearson correlation coefficient. For a detailed / prospective analysis of each pattern found, Hilbert Huang transform is used as a data filter, and others can be used as well.

In the prospective analysis, even when the data from the alpha band were used, the patterns of simultaneous work of increasing zones ($R \geqslant 0.8000$) and inhibition of others ($R \leqslant -0.8000$) are found in other bands (beta, gamma, theta, delta) and in other subjects submitted to test. That is why, as a preliminary exploratory study, this methodology also allows us to narrow down the universe of study and concentrate on the signals coming from the areas that have the higher correlation, whether positive or negative, requiring a very low use of resources. In the experimental case presented in the paper, the results obtained linked the EEG signal with the learning styles of the students who were tested, but also allows the analysis to be linked to other areas of knowledge. The above contributes to explain the diverse, distributed and simultaneous functioning of the brain, expressed by a variety of signals, in this case, by electroencephalography signals (EEG signals).

The methodology here presented significantly contributes to simplify processing, with few resources, in order to identify patterns in a set of data, using global reinterpretation of Pearson correlation coefficient, allowing a variety of detailed studies for patterns of interest, under experimental EEG models.

Acknowledgements

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