Variation of the EEG-Energy in a Second Language Class

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Abstract: The attention, concentration, and anxiety of the students are fundamental in the learning process of a second language. This study proposes to register EEG signals during a second language class to quantify the energy level of the EEG signal and associate it with the attention level along the time. Data was registered while attending to a level 1 English language through 12 minutes. The signals were filtered using a wavelet transform Symlet 6 to analyze two frequency bands: Alpha (8-16 Hz) and Beta (16-32 Hz). The results revealed an increment in the energy on the electrodes AF3, AF4, F3, and F4 in the Alpha and Beta bands between 37.25 and 43.41% of the students, and a decrement between 25.49 and 43.13%. Finally, when analyzing the electrodes T7 y T8, there were an increment of the energy in 35.30% of the students and decrements between 39.22 and 47.60% of theirs.

1 INTRODUCTION

The knowledge and domain of English as a second language in Ecuador has presented a slight improvement in the last year according to the English Profiency Index (EPI) presented by English First (EF) in 2017, locating it in the 55th position, and considering it as a low domain category of the language (First, 2017). The attention, concentration, memory, and anxiety of the students is fundamental in the learning of a second language process; however, the made efforts by the teachers to keep the students' attention during a class are quantified and related to each other using traditional tools as questionnaires, visual manual reports, or monitoring the students behavior through the use of information and communication technologies (ICTs). Monitoring a class through video recordings can provide information about the students-teacher interaction with the finality of training and preparing a teacher for a determined class (Jamil et al., 2015); nevertheless, the behavior in a class does not provide evidence of the attention level that each student presents in the class.

The analysis of electroencephalographic signals (EEG) recorded in people subjected to different external stimuli can reveal important information about the neural processes involved in a learning process. A physiological EEG signal can be recorded second by second, accurately showing changes in attention, fatigue or mental workload in practical work or study environments (Berka et al., 2007). Determining the level of attention of a user using EEG signals has a wide range of applications such as the improvement of a brain computer interface or from the perspective of learning, for the development of linguistic skills, where the attention given to a class is a fundamental element of the process (Cohen et al., 1990; Aliakbaryhosseinabadi et al., 2017). In particular, the learning of a second language has been analyzed from different perspectives, such as the influence of age on learning (Kroll and Tokowicz, 2005), or the application of emotions recognition systems, from another perspective, seeking to reduce anxiety based on language for better development of a conversation in the class environment (Chen and Lee, 2011).

The use of a commercial and portable EEG system is presented in (Poulsen et al., 2017), where the inter-subject correlation of the signals generated by observing a video in a real class is analyzed, demonstrating that this method can be used in a commercial system as biofeedback for the tutor. The implementation of neurofeedback on children with attention deficit is presented in (Kim et al., 2014) through the analysis of the relationship between the relative spectrum of Beta/Theta. Despite the fact that no significant changes were observed in the EEG signal, the effects of the neurofeedback treatment could be evidenced.

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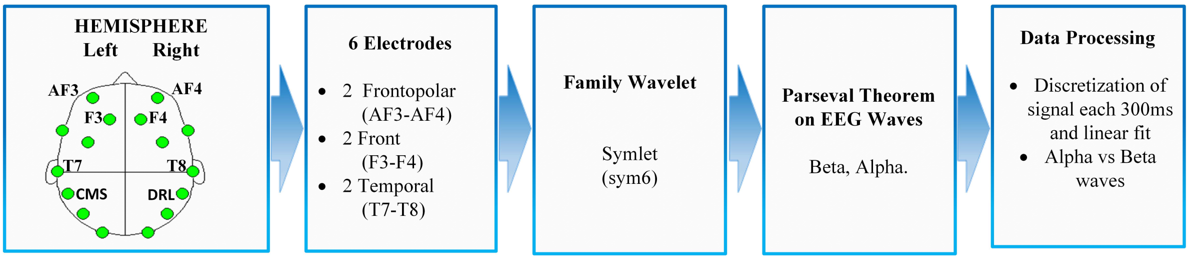

Figure 1: Diagram of the analysis proposal of EEG energy behavior with the passing of time.

Characterizing an EEG signal based on its frequency, it is possible to establish the relation between Alpha and Beta frequency bands and the subject's attention. Beta waves are associated with active thinking, active attention, solving critical problems, or focusing on the outside world, while Alpha waves are associated with an effortless alert state and creativity (Nidal and Malik, 2014). To examine the variation of an EEG signal in a learning process, this study proposes to analyze it during the development of a second language class as a tool to identify the level of attention that a student has throughout the class, associating it with the energy level of the EEG signal.

2 MATERIALS AND METHODS

The data used in this study were obtained from 51 healthy male volunteers, with an age between 18 and 22 years (mean age 19.2 years) previously informed about the objectives and scopes of the study. A database of 51 EEG signals with a duration of 12 minutes each was recorded, under the condition of open eyes while attending a Level 1 English class for university students based on the European common framework. At the end of the class the students had to answer a written standarized test according to the topics studied. The EEG signals were recorded using an EMOTIV EPOC hardware (14 channels) and OPENVIBE software, and then the signal analysis was developed with MATLAB software. A 6-order Butterworth low pass filter with a lower cutoff frequency of 1Hz and a higher cutoff frequency of 45Hz was applied to the stored EEG data. The artifacts higher and lower to $\pm$ 200 uV which werre detected in the signal were removed manually. The sampling frequency of the signals was 128Hz and a Wavelet Sym 6 (Lema-Condo et al., 2017) was applied with 5 levels of decomposition in order to obtain four EEG bands distributed as follows: Beta (16-32) Hz, Alpha (8-16) Hz, Theta (4-8) Hz and Delta (0-4) Hz.

The location of 14 electrodes of the EMOTIV EPOC equipment based on the 10/20 system is observed in the Figure 1. Out of 14 electrodes, 6 have been considered: F3, F4, AF3, AF4, T7, and T8. The average of 51 signals of 12 minutes was calculated for every electrode (e.g., for AF3 $X1_{AF3}[n], X2_{AF3}[n].....X51_{AF3}$, n representing each element of the corresponding signal):

$$\overline{X}_{AF3}[n] = \frac{1}{51}\sum_{i=1}^{51} Xi_{AF3}[n] \tag{1}$$

and the energy analysis was performed with the Parseval Theorem:

$$AF3[n] = \sum_{n=1}^{N} |\overline{X}_{AF3}[n]|^2 \tag{2}$$

where $AF3[n]$ is the energy of AF3, fragmenting $\overline{X}_{AF3}[n]$ into segments of 300 ms (N=38 samples). Finally, a linear regression was applied, and its slope was obtained in order to identify the trend of Beta and Alpha waves.

3 RESULTS

The correlation was calculated between the signals and the time throughout of the 12 minutes of class ranging from -1 as a negative relationship to 1 as a positive relationship. Figure 2 shows the energy level in the left hemisphere (F3, AF3, T7) on the Alpha and Beta waves. The calculated correlation values were statistically significant (p<0.05) in different percentages on each electrode (Table 1).

Table 1: Statistically significance (p<0.05) of the calculated correlation of Beta vs time and Alpha vs time.

Frequency	AF3	F3	T7
Alpha	67%	45%	75%
Beta	51%	59%	63%

Similarly, the correlation between Alpha vs Beta waves was calculated in order to interpret the relationship of these two variables using the criterion stablished in (Nidal and Malik, 2014); figure 3 represents its correlation value. The quadrant I (Q I) shows

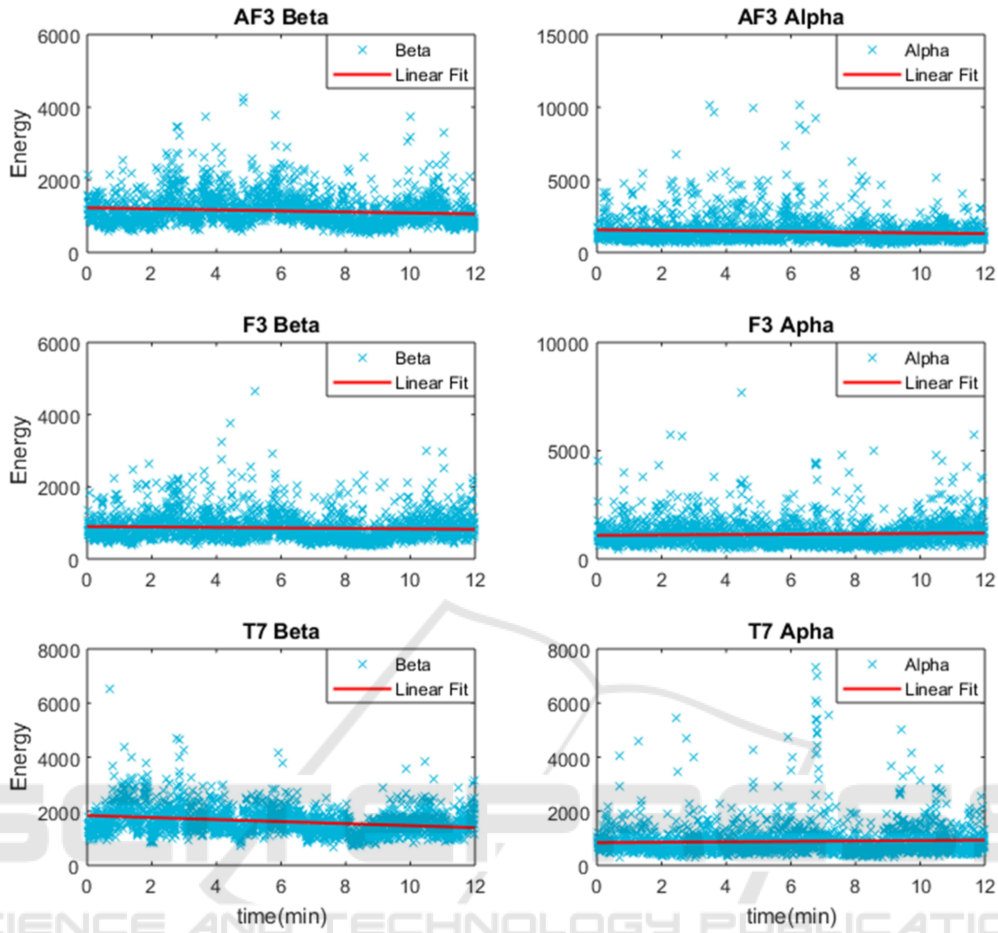

Figure 2: Energy and linear regression on electrodes AF3, F3, and T7, Beta and Alpha waves.

that the person has active attention, considering the values of Beta waves and quiet according to the Alpha waves. Quadrant II (Q II) indicates that the person would be careful with respect to Beta but concerned about Alpha. Also, quadrant III (Q III) shows that the person is worried and stressed, finally quadrant IV (Q IV) shows that the person is distracted with respect to Beta but relaxed with reference to Alpha.

The correlation results of Alpha and Beta waves are shown as a percentage in each quadrant in the Table 1. Considering the relation of Alpha and Beta waves with different attention states, the Q I represents an ideal learning scenario; the student would have active attention and would be relaxed. Q II represents a student segment who are not relaxed in class, possibly due to lack of comprehension in a determine point of the class. Q III represents the student worst scenario because the student doesn't pay attention and also is stressed. Q IV show a student's loss of attention; however, he is relaxed. Taking in account that Q I is the best learning scenario; the analysis showed in this study would allow to the educator obtain biofeedback about the student's attention level, which give him the opportunity to take an adequate decision to improve the class progress. It is important to observe that adapting the methodology of teaching throughout the class it is possible to move the student's attention to Q I. The results show that in terms of electrodes F3, F4, AF3, and AF4, a larger number of students are in the Q I; however, they are rounding the point of zero correlation. This could be considered as a very slight difference; however figure 2 allows to see through the linear regression to tendency along the time, in order to increase the evidence of energy change, more time registered would be necessary in future studies. The second bigger student's group are in the Q III, opposite to I. Electrodes T7 and T8, on the other hand, show a major percentage of students in the Q III, followed by the Q I.

Correlation of the signals energy with the time allows to observe how the energy changes throughout the time, considering Alpha and Beta waves. The

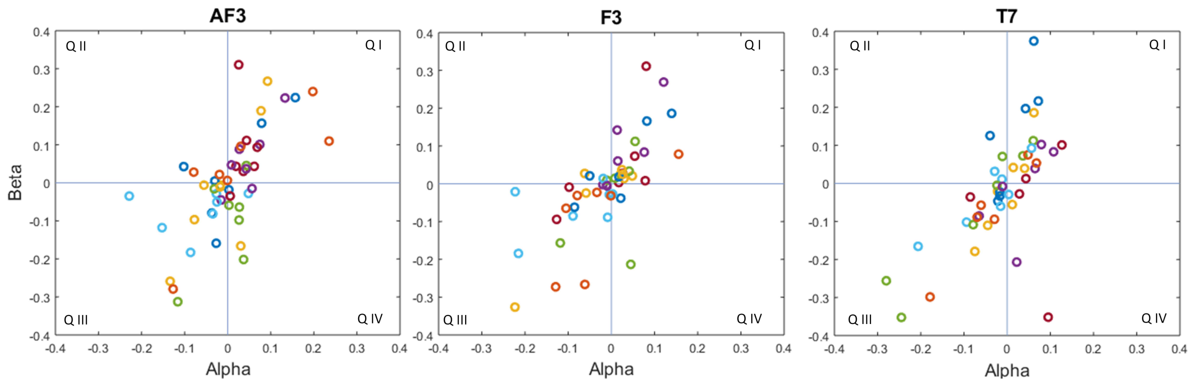

Figure 3: Correlation between Alpha and beta and the position of each patient in the specific quadrant. Each circle represents a student.

Table 2: Percentages of student's location considering the correlation of Beta vs time and Alpha vs time.

Elect.	Q I(%)	Q II(%)	Q III(%)	Q IV(%)
AF3	37.25	11.76	33.33	17.64
AF4	43.13	11.76	35.29	09.80
F3	43.13	07.84	43.13	05.88
F4	37.25	23.52	25.49	13.72
T7	35.29	07.84	47.05	09.80
T8	35.29	13.72	39.21	11.76

percentage of students with a correlation upper to 0 is presented in the Table 3. Moreover, the same table shows the slopes of the linear regression, where the Beta waves are reduced with the passage of time, while the Alpha waves in F3 y T8 are increased. The results of the tests in a scale from 0.00 to 10.00 evidenced that 56.86 % of the students obtained a score ≥ 7.00. This percentage could be represented by the students in the quadrants Q I, Q II, and Q IV, taking into account the data in Table 2 and that the students in this quadrants could increase their attention along the time.

4 CONCLUSIONS

This study proposes to identify a student's attention level in an English class as a second language, analyzing EEG signals. The classes were specially developed for this experiment and the volunteers had a similar level of knowledge about the second language. Considering just the energy field of the EEG signal, it is possible to see an important reduction of the attention since the beginning of the class until the ending of it (12 minutes after) on the Alpha and Beta waves. As a limitation of this study, it is possible to mention that just 6 electrodes were analyzed in the energy ambit taking in account Alpha and Beta waves. Finally, the proposes of this study is a technical analysis of the signals energy throughout the time and it is assumed the relation between Alpha and Beta waves with the relax level and the active attention respectively (Nidal and Malik, 2014).

Table 3: Slope of the linear regression and percentage of the students with a correlation > 0 (left hemisphere).

Score $\geqslant$7.00 = 56.86 [%]		
Electrode	*Corr.* > 0 [%]	Slope $[uV^2/min]$
AF3 Alpha	54.90	-22.99
AF3 Beta	49.01	-14.79
F3 Alpha	49.01	09.43
F3 Beta	50.98	-06.82
T7 Alpha	45.09	08.25
T7 Beta	43.13	-39.12

This study proposes to analyze Alpha and Beta waves of a EEG signal as a biofeedback tool in the process of estimating the attention level during an academic class. Throughout the class, the results revel a decrement of the energy in the Beta waves on the electrodes AF3, AF4, F3, F4, T7 y T8. These results are associated to a loss of students' active attention during the period of class. Alpha waves on the other hand, show an energy increment on the electrodes AF4, F3 y T7 and a decrement on AF3, F4, T8.

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