P300 Speller Based ALS Detection Using Daubechies Wavelet Transform in Electroencephalograph

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Abstract—**The Brain is the main controller of the human body consisting of neurons which generate electrical signals to control the body. Different neurological diseases can cause brain abnormalities such as ALS that affect the electrical activity of the brain which can be seen in the EEG signal. Therefore, these abnormalities can be detected by analyzing the EEG signal. As the Alpha and Beta waves are recorded during the active state of the brain, the effect of abnormalities can be seen in the waves. This study proposes a technique to detect the brain abnormalities and detect ALS syndromes based on Alpha and Beta waves. In this study, the Alpha and Beta waves are extracted from the raw EEG signal by discrete wavelet transformation. Here, the raw EEG signal is divided into several orthogonal wavelets using Doubechis 4 wavelet transform; Alpha and Beta wave frequency components are selected and reconstructed. Then these waves can be compared between different types of ALS patients and normal people based on amplitude and event related potential. The result showed great variation in amplitude as well as event related potential for different ALS patients and normal people. The proposed technique could be used in detecting abnormalities and their severity. It could also help in detecting ALS at a primary stage.**

Keywords—EEG, ALS, Alpha Wave, Beta Wave, Wavelet Transformation, Brain Abnormalities, P300 Speller.

I. INTRODUCTION

Brain Abnormalities caused by different neurological diseases are affecting a large amount of people worldwide. These abnormalities include Amyotrophic Lateral Sclerosis (ALS). It is commonly known as Motor Neuron Disease (MND). Electroencephalogram (EEG) is an important feature to identify as well as analyze such abnormal activities of the brain. It is the graphical representation of the electrical activity happening at the brain which can be measured from the surface. The strength of the signal is measured in microvolts[1]. EEG signals acts as a source of information on how the brain is reacting to different types of works. However, limited number of classifications and evaluation techniques are available to analyze such electrical activities of the brain. The abnormality in EEG signal is identified manually by skilled professionals in maximum of the cases. However, there are very few people and the process is very time consuming. Therefore, this study proposes a novel technique to detect abnormalities for developing some automatic process and computer techniques to be used in this field.

EEG waveforms are generally classified according to their frequency. They are Gamma (31 – 64 Hz), Beta (14 – 30 Hz), Alpha (8 – 14 Hz), Theta (4 – 8 Hz), and Delta (0.5 – 4Hz) [2].

In this study, the classification of abnormalities is proposed based on the characteristic of Alpha and Beta waves mainly. The Alpha and Beta waves can be observed in all age groups during the active state of the mind. Although they are small in amplitude, they can be clearly observed when the brain is working in full efficiency. The Alpha and Beta waves can be affected by different drugs such as barbiturates, benzodiazepines etc. [3] [4].

The Alpha and Beta waves consist of multiple voltage variations which are known as Event Related Potential (ERP). The ERP is a neural signal that shows the structured activity or signal travelling though the neurons for a special activity. The amplitude and abeyance of the consecutive peaks can be used to measure the time duration of subjective processing, and the variance of voltage over the scalp can be used to determine the neuro-anatomical loci of these processes [5].

The overall process of acquisition and feature extraction of the EEG is known as Brain Computer Interface (BCI). BCI involves brain activity monitoring and detection of the characteristics of brain pattern alterations [6].This process includes signal acquisition where the raw signal is collected, processed and converted to digital signal. The next step is the signal processing which includes signal filtering and different type of algorithms for processing the EEG signal variation. Finally, feature of the EEG signal was collected to classify the abnormalities where the desired output is determined and classified [7] [8]. In this study, wavelet transformation is used to extract the desire feature. Discrete Wavelet Transform (DWT) is implemented to decompose EEG signal at root levels of the elements of the EEG signal (Alpha, Beta, Gamma, Theta and Delta) and by using direct decomposition the Alpha and Beta waves are extracted and plotted. The Alpha and Beta waves of the different ALS patients are compared with that of a normal person. The power spectrum density of these waves is also presented to classify the type of ALS patient and their severity.

The paper is organized as follow. Section II presents the data acquisition and methodology of the proposed system. Test outcomes of various patients along with detailed comparisons between patients and normal people are given in Section III followed by the conclusions in Section IV.

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II. Methodology

A. Database

This study used a database recorded from patients in the Neuroelectrical Imaging and BCI Laboratory, IRCCS Fondazione, Santa Lucia, Rome, Italy [9]. The database consists of data from three normal persons and six patients with Spinal and Bulbar Amyotrophic Lateral Sclerosis of different ages and sex. The data was recorded in three different sessions from each patient using 8-16 electrodes. The recorded data was sampled at 256 Hz. Among these nine subjects six represent Amyotrophic Lateral Sclerosis among which three are Spinal and three are Bulbar. The other three persons represent normal healthy person with no brain abnormalities. Data from normal persons was recorded for comparison purposes. Table 1 represents the basic information of the database used in this study.

TABLE 1: BASIC INFORMATION OF THE DATABASE.

Subject Description	**Brain Abnormality**	**Gender**	**Age**	**Source**
ALS Patient	ALS (Spinal)	M	56	NIBL, Italy
ALS Patient	ALS (Spinal)	M	37	NIBL, Italy
ALS Patient	ALS (Spinal)	M	43	NIBL, Italy
ALS Patient	ALS (Bulbar)	F	38	NIBL, Italy
ALS Patient	ALS (Bulbar)	F	60	NIBL, Italy
ALS Patient	ALS (Bulbar)	M	61	NIBL, Italy
Normal Person	None	M	55	NIBL, Italy
Normal Person	None	M	62	NIBL, Italy
Normal Person	None	F	42	NIBL, Italy

B. Wavelet Transform

Wavelet transform (WT) is a useful mathematical tool commonly used for signal processing with many applications in EEG data analysis as well. Its basic use includes time-scale signal analysis, signal decomposition and signal compression [10]. The discrete wavelet transform works with orthogonal wavelets at fixed frequency levels whereas, continuous wavelet transform permits to analyze a signal at random scales, allowing the cutback of the repetition of the obtained coefficients that determines the fixed frequency levels. The WT introduces a useful representation of a function in the time-frequency domain. Basically, a wavelet transform is a function $\psi \in L^2(R)$ with zero average.

$$\int \psi\,(t)\,dt = 0 \tag{1}$$

The DWT of a signal $f(t)$ is then defined as:

$$\mathrm{DWT}\ \psi\,(a, b) = \int_{-\alpha}^{\alpha} f(t)\, \frac{1}{\sqrt{b}}\, \psi^{*}\left(\frac{t-a}{b}\right)\, dt \tag{2}$$

Where $\psi\,(t)$ is known as the mother wavelet and the asterisk (*) denotes complex conjugates, where a and b (a, $b \in R$) are the scaling dilation and translation parameters, respectively. The scale parameter calculates the oscillatory frequency and the length of the wavelet where the translation parameter represents its shifting position.

Processing of EEG by wavelet transformation consists of four sequentially performed procedures[10] as shown in Fig. 1.

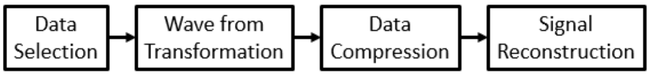


Fig. 1: Processing of EEG using wavelet transformation.

Wavelet Scale Selection: The EEG signal consists of several spectral components of the human brain. For average people, the amplitudes of those spectral components are recorded in the range of 10 to 100 µV where the frequency range lies in the range of 0.1 to 64 Hz. Four bands of EEG signals are commonly used in the clinical analysis such as delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 14 Hz), beta (14 to 30 Hz), and gamma (31-64 Hz). The goal of wavelet analysis is to decompose signals into these frequency bands. Therefore, the EEG is initially divided into sections, or periods using wavelet transform. Wavelets transforming of 512 data points (for sampling rate of 512) produced eight octave scale consisting of 256, 128, 64… 2 data points. Scale 1 represents the highest frequency region with 256 points and subsequent scale indicates the next lower frequency region with half the number of the previous data points and so on. This study used scale 4 with 32 data points for the extraction of beta wave as it provides better resolution for Alpha and Beta waves.

Waveform Transformation: Wavelet transformation is done using Daubechies 4 (db-4) wavelets producing four resolution scales. Daubechies wavelets have increased in popularity for wavelet based signal processing. Daubechies 4 is a standard used for EEG because of its smoothing feature and noise reduction capability for detecting the changes of the EEG signals [9]. The EEG signal is decomposed and the coefficients of the wavelet are stored in array form. Which are then reconstructed and compressed to create the filtered waves. In this study the signals are band limited to 30Hz which is decomposed into details D1-D4 and four approximations A1- A4 as shown in Table 2. It can be observed from the table that the Beta wave is obtained from decomposition level 1 and Alpha wave is obtained from decomposition level 2. [11]

TABLE 2: DECOMPOSED EEG SIGNAL.

Decomposed Signals	**Frequency (Hz)**	**Signal Information**
D1	15-30	Beta Wave
D2	7.5-15	Alpha Wave
D3	3.75-7.5	Theta Wave
D4	1.875-3.75	Delta Wave

Data Compression: Data compression is a process to ignore the unnecessary components of the signal by setting different threshold levels in the characteristics of EEG. The amount of energy restored after compression was then calculated and displayed.

Signal Reconstruction: Each sample is compressed and then reconstructed. Then reconstructed and original signals are showed simultaneously with their compression ratio and restored energy for comparison.

C. P300 Speller

The datasets represent a completer record of P300 evoked potentials with BCI2000. In the session, 6 patients with ALS and 3 normal persons focused on 36 different characters. Users were presented with a 6x6 matrix of characters. All columns and rows of the matrix were continuously and randomly illuminated at 4Hz frequency rate. Two out of 12 illuminations of rows or columns contained the fixed character. The generated response by these random stimuli are different from those recorded by the stimuli that did not contain the fixed character. The EEG signal was digitized at 256Hz and filtered between 0.1 to 30Hz using a band pass filter. Participants were required to memorize seven predetermined words of five characters each by controlling a P300 matrix speller. The columns and rows of the P300 Matrix were randomly illuminated for 125ms, with an inter stimuli interval of 125ms, acquiescent at 250ms lag between the appearance of two stimuli. The participants were placed facing a 15-inch computer screen at eye level approximately one meter in front of them. The angular distance subtended by the speller was of 15 degrees. The recorded data contained the EEG wave, the stimulation level of targeted (column of row containing the desired character) or non-targeted (any column or row not containing the desired character) stimulation and also a number pointing out to which row or column was illuminated in the P300 speller screen.

III. Result and Discussion

This section illustrates the detection and classification results of different ALS patients using EEG signal. The P300 speller had a matrix of 36 different characters organised in rows and columns. Fig. 2 shows this layout of the screen which the user is shown.

Fig. 2: User display of the P300 speller.

If the desired character is ‘P’ and any row or column is illuminated which contains the character ‘P’ results in a targeted stimulation. Any other row or column illumination not containing the character ‘P’ would be considered as a non-targeted stimulation. Fig. 3 shows the numbers assigned to each row and column.

After the EEG data has been collected, the EEG wave can be checked for targeted and non-targeted stimulation and also the position of the row or column for these stimulations.

Fig. 4 shows the EEG signal plotted along with the stimulation level and the position of illumination. The stimulation level and position data were multiplied by 10 for proper viewing.

Fig. 3: Number assignment to all the rows and columns

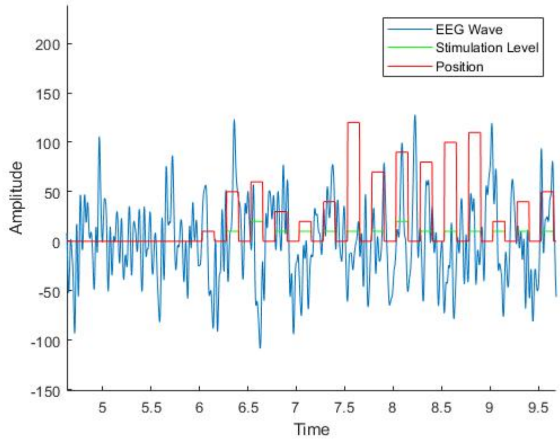


Fig. 4: EEG, Stimulation level and Position plotted together.

So, the data can be taken from the EEG wave when the stimulation level reaches 20 indicating a targeted stimulation and the Alpha and Beta Wave values can be collected from these points for analysis. The position data can also be used to identify which row or column is illuminated.

Fig. 5 shows the Alpha wave of three persons with Spinal ALS. Values were taken when the stimulation level reached 2 and were combined to find the average RMS. The Alpha wave had an average RMS of 1.3246 µV.

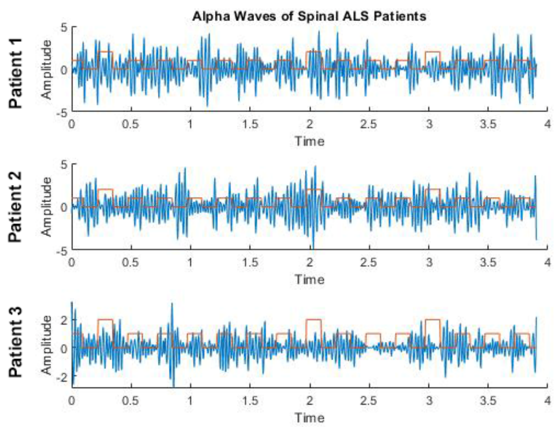


Fig. 5: Alpha waves of three persons with Spinal ALS.

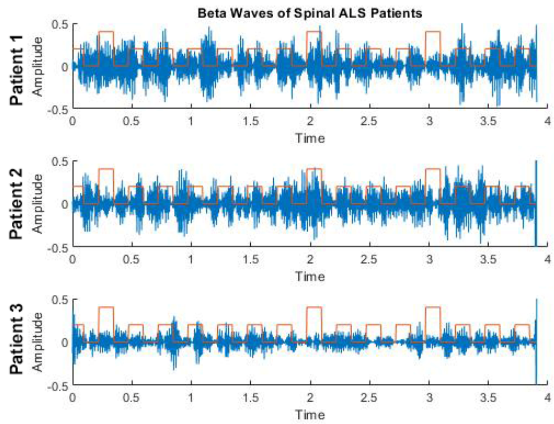


Fig. 6: Beta waves of three persons with Spinal ALS.

Fig. 7 shows the Alpha waves of three persons with Bulbar ALS. Values were taken when the stimulation level reached 2 and were combined to find the average RMS. The Alpha wave had an average RMS of 1.18793 µV. Fig. 8 shows the Beta waves of three persons with Bulbar ALS. Values were taken when the stimulation level reached 2 and were combined to find the average RMS. The Beta waves had an average RMS of 0.14113 µV. The values are found to be even lower.

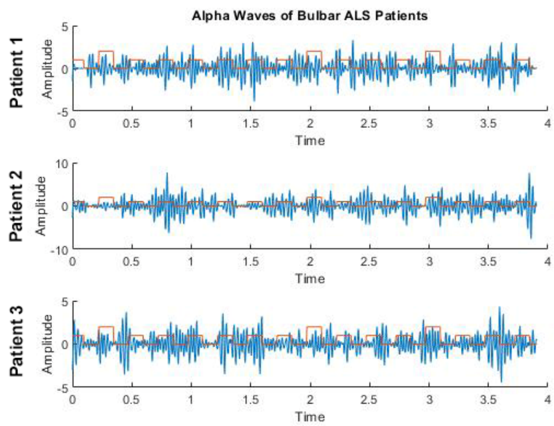


Fig. 7: Alpha waves of three persons with Bulbar ALS.

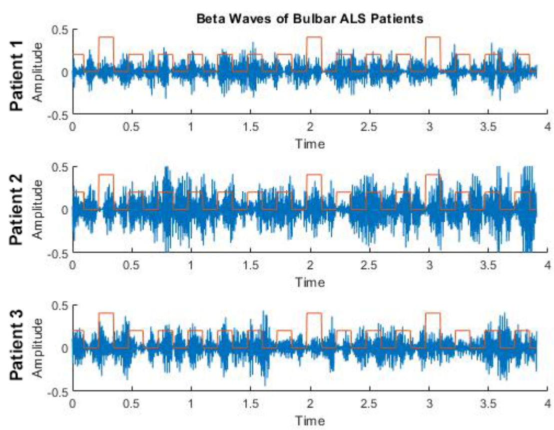


Fig. 8: Beta waves of three persons with Bulbar ALS.

Fig. 9 shows the Alpha waves of three normal persons. Values were taken when the stimulation level reached 2 and were combined to find the average RMS. The Alpha wave had an average RMS of 4.823 µV. Fig. 10 shows the Beta waves of three normal persons. The Beta waves had an average RMS of 0.54546 µV.

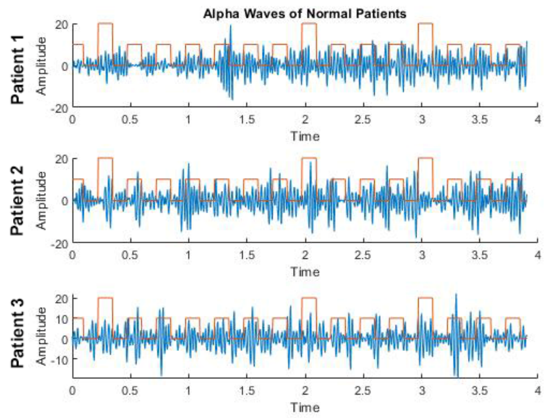


Fig. 9: Alpha waves of three normal persons.

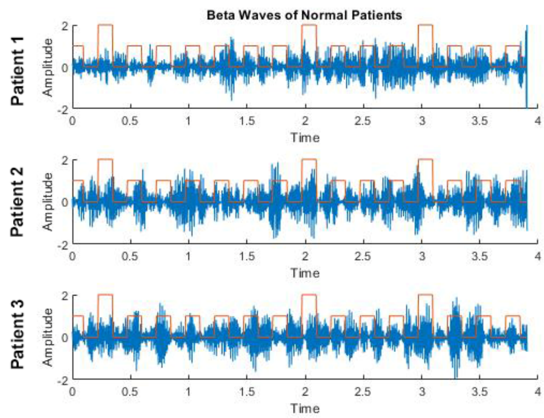


Fig. 10: Beta waves of three normal persons.

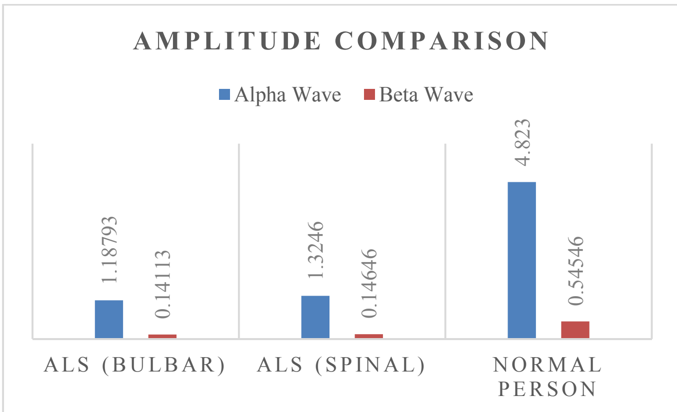


Fig. 11: Comparison of amplitudes of Alpha and Beta waves.

Fig. 11 shows the average RMS of the Alpha and Beta waves of Bulbar ALS patients, Spinal ALS patients and Normal persons. The graph shows that the amplitudes of the Alpha and Beta waves of a normal person are the greatest. Both and Spinal and Bulbar ALS patients have very low values of Alpha and Beta waves among which, Bulbar ALS patients have the lowest. The average amplitude of the

Alpha and Beta waves for all the subjects are given in Table 3.

TABLE 3: DECOMPOSED EEG SIGNAL.

No.	Abnormality	Alpha Average RMS (μV)	Beta Average RMS (μV)
1.	ALS Bulbar	1.0429	0.1160
2.	ALS Bulbar	1.4223	0.1851
3.	ALS Bulbar	1.0986	0.1223
4.	ALS Spinal	1.8827	0.2070
5.	ALS Spinal	1.4653	0.1590
6.	ALS Spinal	0.6258	0.0734
7.	None	4.0716	0.4733
8.	None	5.6036	0.6178
9.	None	4.7938	0.5453

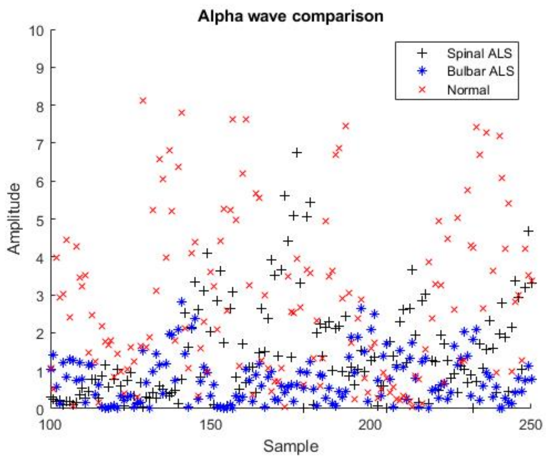
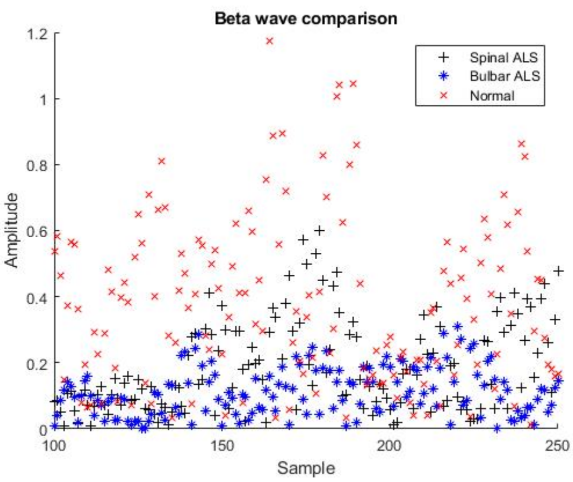


Fig. 12: Comparison of Alpha waves at targeted stimulation.



(b)

Fig. 13: Comparison of Beta waves at targeted stimulation.

Fig. 12 and Fig. 13 shows the scattered plots of Alpha and Beta waves of Spinal ALS patient, Bulbar ALS patient and Normal patient with no abnormalities. It can be seen from the plot that the normal patient has much higher values of Alpha and Beta waves at targeted stimulation.

IV. CONCLUSION

This study is conducted for determining the difference in the Alpha and Beta waves of the EEG signal for different persons with spinal and bulbar ALS along with normal persons for comparisons. Alpha and Beta waves are generated from the electrical activity when the brain is in the active state. The abnormalities caused by neurological diseases such as ALS, affect the electrical activity of the brain and thus affecting the Alpha and Beta waves. In this study the difference in Alpha and Beta waves is determined for two types of Amyotrophic Lateral Sclerosis (ALS) patients and normal persons. The Alpha and Beta waves are extracted from the raw EEG through Discrete Wavelet Transformation by which the EEG data is divided into several decomposed levels according to their frequency. The Alpha and Beta waves extracted from different patients and are compared with the Alpha and Beta waves from normal persons. The power of both the Alpha and Beta waves were found to be much higher in normal persons than in ALS patients having Spinal or Bulbar ALS. Also, these values were found to be lower in Bulbar ALS patients than Spinal ALS patients. So, the proposed study could be used to detect Amyotrophic Lateral Sclerosis and it's type with great accuracy.

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