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Analysis of EEG Signals Using Wavelet Entropy and Approximate Entropy: A Case Study on Depression Patients

Subha D. Puthankattil, Paul K. Joseph

***Abstract*—**Analyzing brain signals of the patients suffering from the state of depression may lead to interesting observations in the signal parameters that is quite different from a normal control. The present study adopts two different methods: Time frequency domain and nonlinear method for the analysis of EEG signals acquired from depression patients and age and sex matched normal controls. The time frequency domain analysis is realized using wavelet entropy and approximate entropy is employed for the nonlinear method of analysis. The ability of the signal processing technique and the nonlinear method in differentiating the physiological aspects of the brain state are revealed using Wavelet entropy and Approximate entropy.

***Keywords*—**EEG, Depression, Wavelet entropy, Approximate entropy, Relative Wavelet energy, Multiresolution decomposition.

I. Introduction

BIOSIGNALS are inherently complex in nature leading to various difficulties in analyzing them for effective clinical diagnosis. Electroencephalogram (EEG), which is the recording of electrical activity along the scalp produced by the firing of neurons within the brain and generally used by the medical professionals as part of the systematic diagnostic procedures, is used in this study on depression patients. It is a noninvasive tool which helps in diagnosing various disorders of the brain and also helps in studying the functional state of the brain. The utility of EEG recordings in diagnosing many neurological diseases, such as epilepsy, tumour, cerebrovascular lesions, depression and problems associated with trauma [1] are well known. There are certain brain disorders which are diagnosed only by visual inspection of such recordings. But the signal of interest used for the case study is that of EEG signals from depression patients which doesn't have characteristic spikes or transients. Hence signal parameters have to be extracted and have to be correlated with the physiological state.

It has been reported by World Health Organisation that depression is among the leading cause of disability worldwide. Depression is a mental disorder. It induces mood variations affecting the thought process and social well being of a person.

The characteristics of depression in the acquired biosignals are not explicitly visible. Therefore advanced signal processing techniques and nonlinear methods are currently being employed to extract feature which would assist the physicians in clinical diagnosis.

Frequency analysis of sleep staging revealed that the mean REM latency for the normal controls was somewhat lower, but did not differ significantly from that of the depression patients [2]. It was claimed that the Wavelet entropy (WE) and sub band segmentation could characterize the degree of disorder and complexity of the EEG signals recorded from depression patients [3]. There are innumerable contradictions and inconsistencies with different concepts of various disorders still existing in depression studies [4], [5]. There have been some studies on depression based on linear methods considering amplitude, power and frequency [6]. Wavelet entropy (WE) was introduced as a new tool for the analysis of short duration brain electrical signals. The results demonstrated that WE could differentiate between specific physiological brain states under spontaneous or stimulus-related conditions [7]. Relative Wavelet Energy (RWE) calculated from the energies of details and approximations is used as a tool to select suitable wavelet for artifact removal in EEG [8]. Nonlinear analysis provides a promising tool for detecting relative changes of emotion during the perception of music [9].

With the advent of methods of nonlinear dynamics, new concepts and powerful algorithms were developed to analyse brain electrical activity. Various nonlinear approaches: Approximate entropy (ApEn), Fractal dimension (FD), Correlation Dimension (CD), Kolmogorov-Sinai entropy, Renyi's entropy, Sample entropy, Spectral entropy, Lyapunov exponent (LE), Hurst exponent etc. are found to be effective in the feature extraction of EEG signals. Process complexity increases with increasing value of ApEn [10]. The performance of neural network classifier in detection of an epileptic seizure using ApEn as the input feature was analysed [11].

In this work, wavelet analysis is carried out using the wavelet Coiflet 5. Relative Wavelet Energy calculations are carried out for all levels of details and approximation, obtained by conducting an eight level decomposition. Wavelet entropy which is a function of time is then evaluated from the values of RWE. Quantitative analysis of EEG signals of depression patients using nonlinear method is subsequently carried out using Approximate entropy.

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II. Methodology

A. Data Used

The EEG signals are acquired from 30 depression patients and 30 age and sex matched normal controls in the age group of 20-50 years from the Psychiatry Department of Medical College, Calicut, Kerala, India. The cases considered for the study are the ones with unipolar depression who are neither under the influence of any substance abuse nor with any significant medical illness. Bipolar EEG recordings were carried out at locations FP1-T3 (left half) and FP2-T4 (right half) of the brain using a 24-channel EEG measuring instrument (RMS-24) for a duration of 5 minutes each, under eyes closed and eyes open condition in a resting state. The EEG signal recording is based on the International standard 10-20 electrode placement system.

Informed written consent was obtained from all the subjects who participated in the study and medical ethical committee approval was taken prior to the study. The signal is sampled at the rate of 256 Hz and also notch filtered at 50 Hz to remove the power line interference. Figs. 1 and 2 represent the EEG signal of a normal control and that of a depression patient respectively.

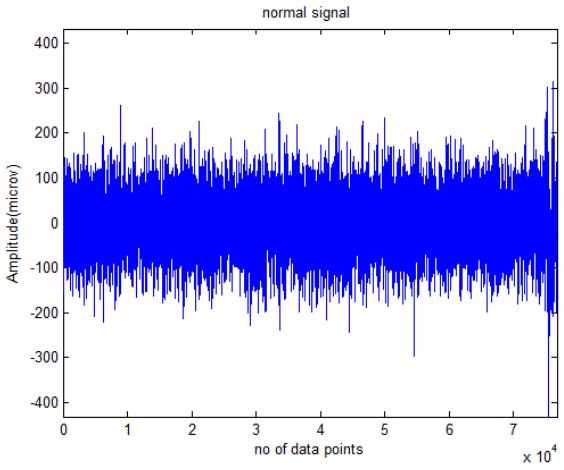

Fig. 1 EEG signal of a normal control

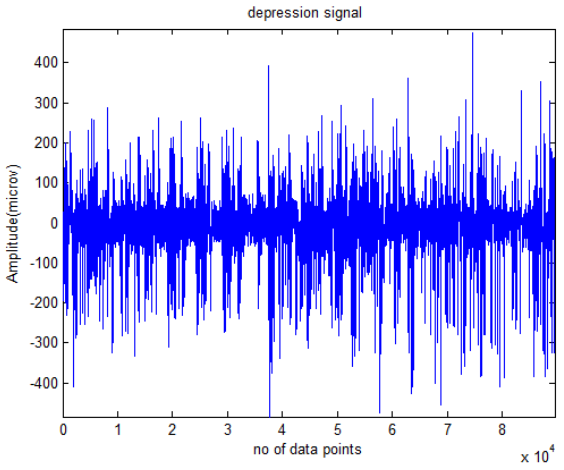

Fig. 2 EEG signal of a depression patient

B. Relative Wavelet Energy

DWT based multiresolution analysis is employed in this study using the wavelet Coiflet 5. An 8-level decomposition is carried out to classify the frequency bands into appropriate detail levels and approximation level. The multiresolution analysis decomposes the signal into details which are the high frequency components and approximations, the low frequency components. They are obtained by successive convolution with high-pass and low pass filtering of the time domain signal respectively [12]. An 8-level decomposition is adopted in this study with D1 (64-128Hz) and D2 (32-64Hz) corresponding to Gamma band, D3 (16-32Hz) corresponding to Beta band, D4 (8-16Hz) corresponding to Alpha band, D5 (4-8Hz) corresponding to Theta band while D6 (2-4Hz), D7 (1-2Hz), D8 (0.5-1Hz) and A8 (0-0.5Hz) corresponding to Delta band. Energy calculations are performed using Parseval's theorem.

The similarity between different segments of a signal can be detected using RWE [13], [14]. Relative Wavelet Energy (RWE) is used for characterizing the various frequency bands of both normal controls and depression patients.

The energy of wavelet coefficients $d_{n,j}$ is the energy at different decomposition levels (from 1 to N) which is a representation of the energy of the detail signal at each resolution level, n is given by

$$E_n = \sum_j \left| d_{n,j} \right|^2 ; n = 1 \ldots N \tag{1}$$

The total energy of the signal for all levels is given by

$$E_{total} = \sum_{n=1}^{N} E_n \tag{2}$$

Hence the Relative Wavelet Energy (RWE) is defined as

$$\rho_n = \frac{E_n}{E_{total}} ; n = 1, \ldots, N \tag{3}$$

The energy distribution of the signal at different frequency bands are obtained from the above equation [15].

C. Wavelet Entropy

Wavelet entropy (WE) is calculated to give information about the dynamics in the EEG records [16], [17]. The Wavelet entropy as a function of time is calculated as

$$WE = -\sum_{n=1}^{N} \rho_n \ln(\rho_n) \tag{4}$$

where N is the wavelet decomposition level, from level 1 to level N.

D.Approximate Entropy

Approximate entropy (ApEn) quantifies regularity and complexity and has its application in the analysis of time series data. ApEn measure the (logarithmic) likelihood that runs of patterns that are close remain close on next incremental comparisons.

For a time series of N data points, $\{u(i):1 \le i \le N\}$, form vector sequences $x(1)$ through $x(N\text{-}m\text{+}1)$, defined by $x(i) = [u(i),..., u(i+m-1)]$. These vectors represent m consecutive u values, commencing with the i^{th} point. m is the length of compared runs. Let B_i be the number of vectors $x(j)$ within r of $x(i)$ for a window length m and let $A_i$be the number of vectors $x(j)$ within r of $x(i)$ for a window length $m+1$, where r is the tolerance for accepting matches [18]. The function $C_i^m(r)$ is defined as:

$$C_i^m(r) = \frac{(B_i)}{(N-m+1)} \tag{5}$$

$C_i^m(r)$ is the probability that any vector $x(j)$ is within r of $x(i)$. The function $\Phi^m(r)$ is defined as:

$$\Phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} \ln C_i^m(r) \tag{6}$$

where, $\Phi^m(r)$ is the average of the natural logarithms of the functions $C_i^m(r)$.

For finite data sets,

$$ApEn(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r) \tag{7}$$

Larger values of ApEn represent the irregularity in u [19]. The values of m and k adopted in this work are 1 and 0.2 respectively [20], [21].

III. Results

The dynamics of the brain of both normal controls and depression patients are analysed using WE and ApEn. Time frequency analysis is initiated in this work with the calculations of RWE. The relative energy associated with the different frequency bands in the EEG signal are revealed by the Relative wavelet energy calculations.

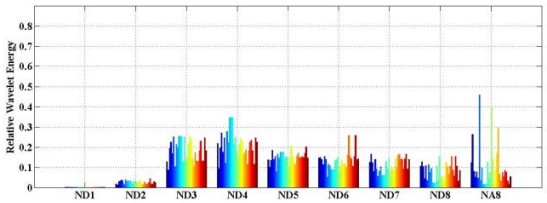

Fig. 3 RWE of all frequency bands of normal controls

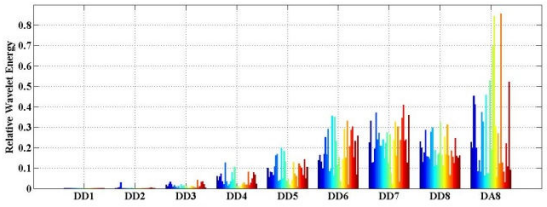

Fig. 4 RWE of all frequency bands of depression patients

Figs. 3 and 4 represent the RWE distribution among all frequency bands of normal controls and depression patients respectively. Table I shows the values of RWE (in percentage) at each decomposition level for normal and depression patients.

TABLE I
RWE in Percentage for an 8- Level Decomposition of the Acquired EEG Signal

Wavelet Decomposition Level	Normal RWE (%)	Depression RWE (%)
D1	0.06	0.00675
D2	2.6	0.22
D3	18.2	1.34
D4	21.3	4.07
D5	15	8.55
D6	13.2	17.8
D7	11	22.3
D8	8	18.4
A8	10.4	27.4

Relative Wavelet Energies are higher for normal controls in gamma (D1and D2), beta (D3), alpha (D4) and theta (D5) bands (Table I). RWE is significantly higher for depression patients in the Delta band. Higher values of RWE in alpha band indicate larger mental activity while the effects of depression are more prominent in the lower delta band of 0-4 Hz.

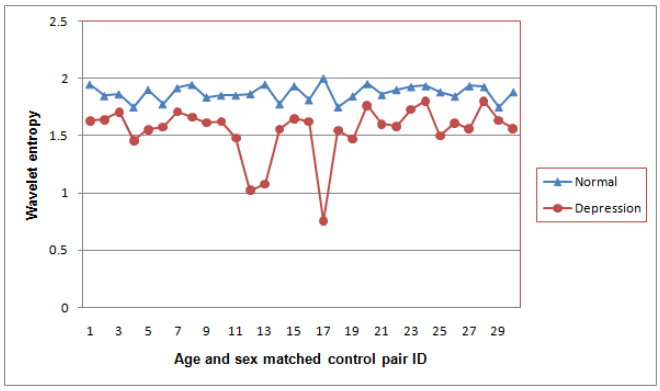

Fig. 5 Wavelet entropy of normal and depression patient

While comparing the Wavelet entropy of normal and depression cases (Fig. 5), it could be inferred that WE acts as a good indicator that can differentiate the various brain states of normal and depression patients. The observation of a decrease in the WE in the EEG signals of depression patients, indicates a more rhythmic and ordered behavior. These quantifiers

based on time-frequency methods help in a better understanding of the brain dynamics.

The overall complexity of EEG signals is very well reflected in the calculated values of ApEn. Fig. 6 shows the calculated values of the 30 depression patients and 30 age and sex matched normal controls.

The normal controls are found to have a higher value of ApEn compared to depression patients. ApEn values are markedly low for depression controls compared to the healthy group in the present study. A low value of ApEn indicates the predictability and regularity in a time series, whereas a high value of ApEn indicates unpredictable and random variation. The results of ApEn are indicative of the complexity of the brain activity or higher brain activity in normal controls, while the signals from depression patients are found to be less complex.

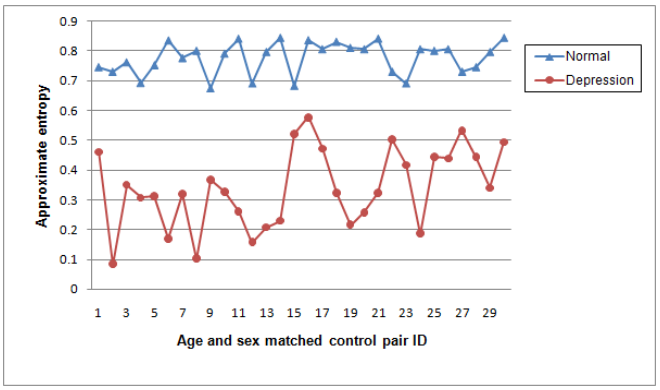

Fig. 6 Approximate entropy of normal and depression patient

IV. Conclusions

Time-frequency and nonlinear methods have been employed for the analysis of EEG signals of depression patients and age and sex matched normal controls. We have developed and implemented an eight level decomposition method for the classification of the EEG signal into various frequency bands. Relative Wavelet Energies are calculated for all the frequency bands of normal and depression EEG waveforms. Larger values of Wavelet entropy for the normal controls, obtained from the calculations of RWE, indicated a highly disordered state, leading to increased levels of mental activity. The nonlinear measure of Approximate Entropy also showed a larger value for normal controls compared to the depression patients. Hence the two quantitative measures investigated: one of time frequency analysis and the other of nonlinear measure clearly prove that the mental activity of human brain can be very well differentiated. This could be explored further in the development of automated signal analysis for clinical prognosis.

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