International Conference on Intelligent Technologies & Science - 2022
(ICITS-2022)

Application of Data Mining using Spectral Features for Detection of Sleep Disorder

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Abstract: This paper represent the detailed description of several methods identified for monitoring sleep behavioural patterns in order to understand the experimental basis and forming a strong theoretical background towards analyzing these EEG signals. EEG data has proved to reflect the activities of brain over all the section with respect to human activities. They are useful in both cases that is in awakening states and also in the sleep stage. Most of the brain disease is due to the deterioration of brain cells. The EEG data is used in this work to generate some frequency based energy level features for RBD patients and normal persons. It has been found that the percentage energy level may be considered as parameter to distinguish healthy and defected EEG data due to sleep disorder.

Keyword: Electroencephalogram, Sleep stages, Quality sleep, RBD.

1. Introduction:

In the past twenty years abundance of research work is published on new proposals and algorithms on biomedical signals like EEG , ECG etc which supports the use of power estimation in frequency domain for several disorders detection and diagnosis. One of the article published by Penzel et al. demonstrated the use of single-lead ECG for diagnosis of sleep disorders [10]. After this many literature is published remark ably on such king of ECG data for simplifying the use of instruments for data recording and reducing computation complexity. All of such kind of work focused on extracting the patterns or called as features. The selection of the optimal parameter of calculations is universally accepted in numerous kinds of advanced machine learning techniques. Heart-rate-variability (HRV) [11], consecutive heart beat (RR) time period, and respiratory data records are extremely used for finding outsets of the feature to use in pattern recognition and machine learning[12]. These kind of biomedical data features are used in modern pattern recognition application in diagnosis of several human disorders and disease using variety of domains of time and frequency [13, 14].Appropriate features are to be significantly sorted out for simple and fast statistical equations [14] or evaluation methods [12,15].One of the approach is principal component based extraction of feature that helps to dimensions and improve detection accuracy of diagnosis of specific disease. In this work focus is given on diagnosis of sleep disorders. Sleep is very crucial activity because in a lifespan time sleep covers 1/3 part of the lifetime. Sleep is important like other activities such as eating, drinking and breathing. In the moments under sleep body and brain repair itself by interacting through hormones, muscles neurons and memory. sleep disorder occurs when someone cannot sleep properly it results in lose function of the body organs and muscles. The common benefit of the sleep covers physical, emotional and psychological impacts. Improper sleep damages us in physical, emotional and psychological aspects. Nearly 84 types of sleep disorders are observed like narcolepsy, insomnia, sleep-apnoea and restless-leg-syndrome etc [1].

2. Related Work:

Epilepsy is a group of neurological disorders that are characterized by an enduring predisposition to generate recurrent seizures and can affect individuals of any age. Epilepsy arises from the gradual neurobiological process of 'epileptogenesis' [1], which causes the normal brain network to fire neurons in a self-sustained hyper-synchronized manner in the cerebral cortex. According to the World Health Organization (WHO), 70 million people worldwide have epilepsy and epilepsy trails only migraine, stroke, and Alzheimer's disease in the list of the most widespread brain diseases [2]. The seizures caused by epilepsy are debilitating and disrupt the day-to-day activities of the patients, and are associated with an increased risk of premature mortality. The dearth of neurologists in many countries complicates the management of epilepsy—especially in the developing countries where the neurologists are in short supply.

Hidalgo-Munoz et al [3] studied EEG signals of 26 females while watching emotional images from IAPS. This study considered emotions according to the valence-arousal model. In the processing step, they used spectral turbulence (ST), a method which was inspired by ECG studies. Results show that the left temporal lobe has considerable activity during emotion elicitation.

Weinreich et al [4] measured variations of alpha frequency band in frontal lobe from an oddball paradigm. Participants were asked to describe each image regardless of the emotion of the image. 16-channel EEG signals were recorded from 20 female and 8 male participants.

Bozhkov et al [5] considered valence-arousal model for emotions and recorded EEG signals from 26 females viewing IAPS pictures. They used Echo state networks (ESN) to cluster and classify positive and negative emotions. They obtained the desired results and demonstrated the performance of their proposed method.

3. Methodology:

Step 1: Load the EEG data

Step 2: EEG Signal Extraction

We have downloaded one minute data from physionet bank on sleep disordered breathing in all the sleep stages and cut the selected channels:

ROC-LOC,
C4-P4,
C4-A1,
F4-C4,
ECG1-ECG2,
EMG1-EMG2,
P4-O2.

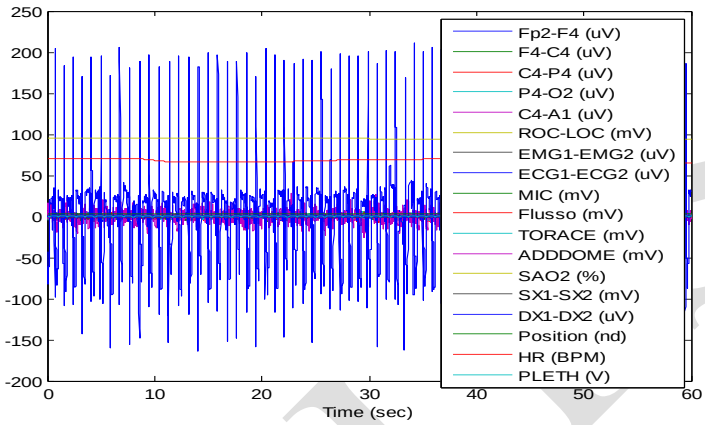

Fig. 1. Extraction of the signal

Step 3: Removal of Noise Component (if necessary)

The high frequency component of signal's FFT is actually the not required for biomedical signal and it represents signal ripples at higher frequency, so by making it to zero, we can remove high frequency ripple component

Step 4: Removal of high frequency components through low pass FIR filter of cut off frequency of 25 Hz. Removal of high frequency component using Low pass fir filter of cut off frequency 25 Hz. Fir filters are designed using the Signal Processing functions and Direct-Form II Transpose Filter .Fir filter function 'filtfilt' performs zero-phase digital filtering by processing the input data, in both the forward and reverse direction.

After filtering the data in the forward direction, 'filtfilt' reverses the filtered sequence and runs it back through the filter. The result has the following characteristics:

(i) Zero-phase distortion
(ii) A filter transfer function which equals the squared magnitude of the original filter transfer function

Step 5: PSD Estimation (Welch Method)

PSE is most important operation area in Digital Signal Processing. Welch method is nonparametric method that comprise the periodogram that have the choice of possible application using the fast Fourier Transform. The periodogram is an approach of estimating the autocorrelation of finite length of a signal. The periodogram procedure based on Welch method is capable of contributing good resolution if data length samples are chosen optimaly. It can be noticed that PSE based on the Hamming give better results than Hanning window.

The periodogram estimate of the PSD of a length-L signal $x_L[n]$ is

$$P_{xx}(f) = \frac{1}{LF_s}\sum_{n=0}^{L-1} x_{L(n)e^{-j2\pi f_n/F_y}}$$

Where, F_s is the sampling frequency.

The actual figuring of Pxx(f) can be executed only at a finite number of frequency points, and normally apply FFT. Most applications of the periodogram method compute the N-point PSD estimate at the frequencies:

$$f_k = \frac{kF_s}{N} \qquad k = 0,1 \ldots, N-1$$

Step 6: Area corresponding to delta, theta, alpha and beta bands are calculated using Trapezoidal Integration method to calculate average power.

Area Estimation of delta, theta, alpha, gamma frequency bands are evaluated by using Trapezoidal method. Delta (δ) wave having frequency range 0.5 to 4 Hz , theta (θ) wave having frequency range 4 to 8Hz, alpha (α) wave having frequency range 8 to 13 Hz, beta (β) wave having frequency range 13 to 30 Hz.

Step 7: Power ratios are calculated by dividing average power of individual sleep wave frequency band by the total average power of all the bands.

In order to determine the average power for individual frequency bands for the full night, a 60 s window was enforced to the start of the signal, after the basic steps of DC component removal and low pass filtering were executed. The average power in a given frequency band approach uses a rectangle approximation of the integral of the Hs signal's power spectral density (PSD). The average power is the total signal power and the total average power is enclosed in the

one-sided or two-sided spectrum. The PSD estimate was computed for the 60s window and average power of frequency bands delta, theta, alpha and sigma were determined and then normalized.

Step 8: Difference in power ratios of analogous frequency bands are evaluated.
Step 9: Slide the window and repeat the step 5 to 8 for the entire signal duration.

4. Result and Discussion:

We have used a sleep data consist of 20 type of signal. Out of these signals we have taken EEG channels for analysis of sleep disorder. For example figure 2 shows the extracted EEG signal of channel 3 of n1_edfm.mat i.e. ROC-LOC in microvolt level (μV).

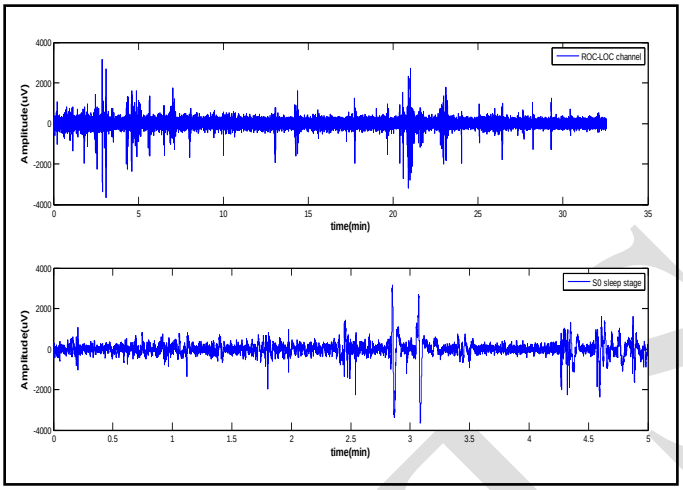

Fig. 2 (a) ROC – LOC (EEG signal) and (b) its plot for sleep stage S0.

Figure 2 shows a plot of EEG signal of a normal subject Normal 3 with data base name 'n3_edfm.mat' it shows the ROC-LOC channel it is 3rd channel of given data and in figure 2(b) we have shown the clipped signal of duration 5 min consisting of EEG signal of respective channel for sleep stage S0. Here total signal is of duration of 30 min ,sampling frequency 512Hz , Sleep stage start time is 22:9:33 and end time of S0 is 22:14:33.We can also extract in other sleep stage clips by the knowledge of t start and t end of that particular stage. We have also processed the data of REM sleep stage. Similarly we have taken signals of subject with RBD sleep disorder for S0 and REM stage as shown in figure 2(e and f) and 2(g and h).

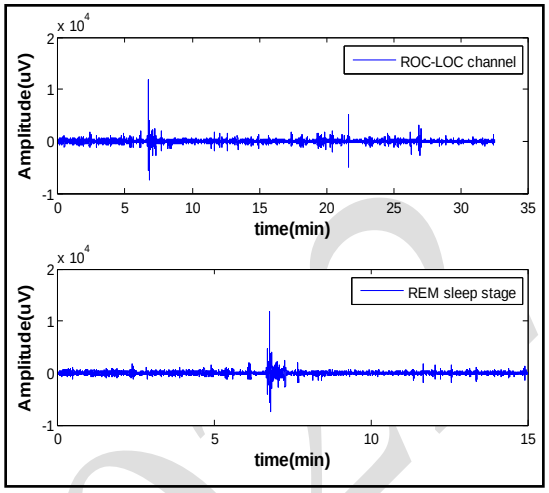

Fig. 2 (c) ROC – LOC (EEG signal) and (d) its plot for REM sleep stage for normal case.

Figure 2(d) depicts the clipped signal of duration 15 min consisting of EEG signal of respective channel for REM sleep stage.

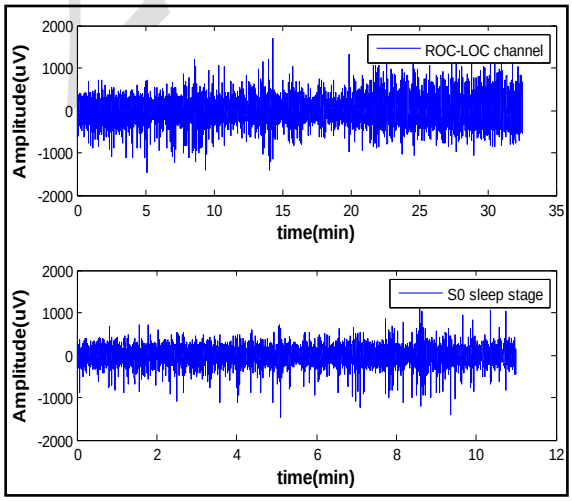

Fig. 2 (e) ROC – LOC (EEG signal) and (f) its plot for S0 sleep stage for patient with RBD disorder

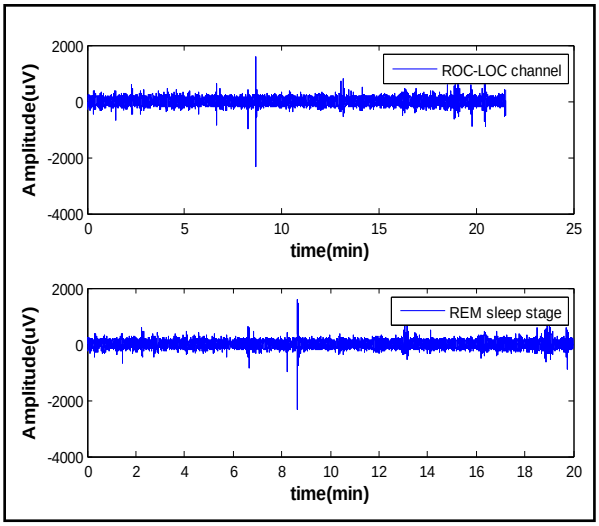

Fig. 2 (g) ROC – LOC (EEG signal) and (h) its plot for REM sleep stage for patient with RBD disorder.

5. Conclusion:

The developed approach can subsidize to better objective interpretation of the EEG activity at the time of quiet and active sleep in full term healthy human beings. It was shown, that the time profiles of different patients and normal patients reflect the structure of EEG signal during quiet and active sleep. The procedure is capable of working even in the presence of different PSD estimation methods. New measures of sleep recording can be obtained by moving to various sleep centers or hospitals. By that the whole night sleep data can be attained and the process of extracting the data cal also be done. EEG recording is done through the EEG cap in which gel is there, the originating brain's electrical activity is captured.

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