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Comparative Approach to Detect Nocturnal Frontal Lobe Epilepsy Sleep Disorder through Frequency spectrum and its Energy Levels

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Abstract

EEG data has proved to reflect the activities of the brain over all the sections with respect to human activities. It is useful in both cases that are in awakening states and in the sleep stage. Most of brain disease is due to the deterioration of brain cells. In this research work, EEG data is used to generate some frequency-based energy level features for NFLE (Nocturnal Frontal Lobe Epilepsy) patients and normal persons. After experimentation, it is found that the percentage of energy levels may be considered as a parameter to distinguish healthily and defected EEG data due to sleep disorder. During this study, it is also found that S0 is proved to be helpful in the diagnosis of NFLE sleep disorder because in this stage the percentage energy level is to be high for alpha waves for patients having a sleep disorder. The results show that the average percentage energy level in NFLE patient is 0.009872 while in normal cases it is 0.0010148.

Keywords: EEG, Sleep disorder, NFLE, Pattern Recognition, Data Mining;

1. Introduction

Human life is influenced by 2 types of health (1) mental health (2) physical health. Treatment and check-ups of physical health are possible in many general ways, while both mental health treatment and testing are parts of a complex process [1]. Mental health depends on many factors such as the quantity of food, family problems,

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unemployment, environment, workload, etc. Along with scientific development, mental diseases also got important in medical science. Sleep problems have become important constituents of these mental diseases. To a large extent, the origin of mental diseases depends on the quality of sleep. Sleep disorder occurs when someone cannot sleep properly it results in loss of function of the body's organs and muscles. According to scientific research, sleep is divided into two parts. The first one is REM (Rapid Eye Movement), in this kind of sleep, human eyes keep on moving. Most dreams are part of this type of sleep. The second one is NRAM (Non-Rapid Eye Movement), in such sleep, a man doesn't see dreams. In such sleep, the brains are in a state of complete rest. The NRAM is also divided into several stages – S1, S2, S3, S4. These stages of sleep are further, gradually, divided into light and deep sleep states [1]. In this research, attempts have been made to identify NFLE disorder by applying a comparative approach with the help of energy levels of the EEG spectrum. NFLE disorder most commonly occurs during S0 and REM stages of sleep. The first reactions or electrical impulses vibration starts from the frontal lobe for this type of disorder and ends with seizures.

2. Literature Review

All previous research can be divided into two parts: (1) Assessment of sleep quality with the help of wearable devices, (2) Assessment of sleep quality by automated equipment. Understanding the usefulness of sleep in human life, and assessing the quality of sleep accurately has been a special subject matter for researchers of all times. Several methods of assessing sleep quality have been developed from time to time, such as initially testing the movement above the subject's bed by load cell sensor grid, and understanding the quality of sleep by testing the leg movement using a linear classifier [1]. In this experiment, sleep stages were classified with 79.3% accuracy. In the year 2016, wearable devices made subjects feel uncomfortable due to which their sleep quality could not be estimated properly. So in this research, 48 FSR (Force Sensing Resistors) were installed under the bed and Sleep quality was tested under different error rates using class logistic regression. In this experiment, 95.8%, 90.2% and 88.5% accuracies were found under the 4.2%, 9.7%, and 11.5% error rates respectively [2,3]. According to Tseng et al. [4], an accurate assessment of sleep quality cannot be done by excluding electrical impulses originating in the human brain. In this experiment, electrical impulses originating in the human brain were recorded and the frequency of these electrical impulses was measured, and the quality of sleep was understood based on the power of these frequencies. Here EEG signals were recorded through a Bluetooth-based device with the help of which the recorded data was sent to cloud storage for further processing. Since the brain signals are of very low voltage, the voltage signals were converted into the frequency with the help of DAQ100 module for good processing. In the year 2012, it was believed that a person spends one-third part of his entire life sleeping. Understanding the importance of sleep in this research, many mathematical calculations were done and the formula of sleep index was calculated. And it was assumed that for different genders, estimation of sleep quality in different age groups is possible only under different sleep indexes [5]. Technology like IoT (Internet of Things) has made research related to the quality of sleep to a great extent easier. Through the research work conducted in the year 2016, IOT technology created a different image for itself. In these experiments, the possibility of adding noise signals to the sleep quality data was found to be very low which made the sleep quality measurement calculation easier [6]. Realizing the importance of sleep in human life, a momentum in sleep-related research came when ultrasonic technology assessed the quality of sleep by examining the sonar-generated movement on the subject's bed by an automated appliance. In this experiment, 62 subjects were tested. In this experiment, sleep was tested at different sleep stages and results with 87%, 89%, 84% accuracy were found in wake time, REM, and deep sleep stages, respectively [7]. Both methods of assessing sleep quality (by wearable devices & by automated devices) have their own importance. Scientific research believes that wearable devices make the subject feel uncomfortable and it is a complex process to assess the quality of sleep properly. Whereas many noise factors are added to record sleep data by non-wearable device. Accurate assessment of sleep quality can be done by processing electrical impulses originating in the brain. The deep sleep index formula was calculated with the help of EEG recordings and force sensors, which is given below,

Deep Sleep Index (DSI) = 0.55 * No. of Small Movements + 1.05 * No. of Medium Movements + 1.02 * No. of Large Movements.

In this research work, 95.7% accuracy was recorded for deep sleep [8]. In the research conducted in the year 2018, it was believed that the breathing pattern is an important parameter in the quality of sleep. In this experiment, Sleep Disorder Breathing Algorithm was written and after implementation, 93% accuracy was obtained [9]. Sleep data were collected using I-Sleep sensors in an experiment conducted in the year 2019 and machine learning algorithms k-nearest neighbor, logistic regression and SVM were used to test the sleep quality. Results found 95.2%, 94.9%, 94.7% and 95.8% accuracy by k-nearest neighbor, logistic regression, and SVM, respectively [10]. In another research conducted in the year 2019, it was assumed that different sleep patterns are seen at different locations, for different age groups & different genders. In this research, electrical implants were divided into different frequency ranges - 0.5 - 4, 4- 8, 8-12, and 12-32 Hz, termed delta, theta, alpha and beta respectively. The research found that the fluctuation in delta frequency is higher in females than in males. In this experiment, 10-20 instruments were used for EEG recordings [11]. According to Ravan et al. [12], frequent use of the 10-20 system can cause brain-related disorders and therefore such experiments should be avoided. Ravan introduces a Vagus Therapy. This research found that daily use of Vagus Therapy can enhance sleep quality. In this experiment, 90% accuracy was achieved by using the SVM algorithm [12]. All the researches in assessing the quality of sleep are in order to make experiments cheaper and simpler. In this order only, in the year 2017, a mobile application was developed, which was capable to measure major factors even like heart rate also. In this experiment the architecture of the application system is divided into 4 parts (1) data collection, (2) pre-analysis (3) application role & (4) result [13]. Most scientific researchers believe in the processing of EEG signals. Researchers suggest that EEG readings repeat themselves at a particular interval. Scientists call it Periodic K-alpha. Many scientific types of research on these Periodic K-alpha confirm that these Periodic K-alpha are found in different patients in different diseases. Thus sleep quality index can be calculated with the help of Periodic K-alpha [14]. In 2011, research on narcolepsy patients considered that the Cyclic Alternative Pattern (CAP) is an important parameter in sleep quality assessment. Different CAP patterns were tested in all aspects of narcolepsy patients in this experiment. For a better understanding of the Literature review all previous works can be divided in two ways (1) Literature based on wearable devices, (2) Literature based on self-operating devices.

3. Methodology

To identify NFLE sleep disorder, step by step signal processing is needed. To understand the concept a flowchart of work is defined in Fig 1.

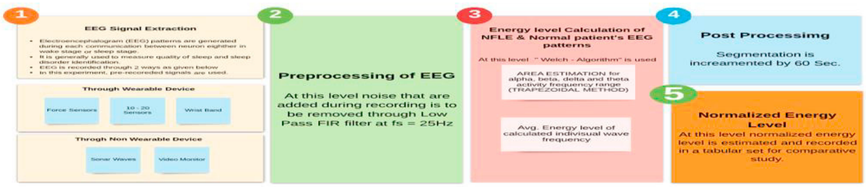

Fig. 1. Step wise data processing plan

As above flowchart shows the step wise processing of EEG to calculate the power spectrum of different waves for Normal and NFLE patients to differentiate the NFLE patient from the normal one.

In this research work MIT data set is used. As the recorded data set is used so some preprocessing steps are needed for further analysis. Here as given in Fig 1 all process is done accordingly.

3.1. Load the signal

The command known ad load (file name) on the data is loaded and saved in tool MATLAB space under cache memory and details of given signal and are scanned from another file ‘n1_edfm.info’. load (mat Name) command gives a data matrix in workspace memory with name ‘Val’ it has 20 channels in row wise manner and each EEG channel of length 1000000 samples. here enlarged view for initial 1000 samples are shown in Fig 2.

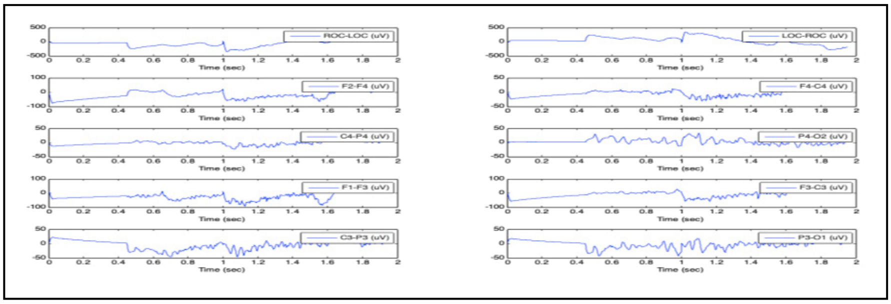

Fig. 2. Plot of enlarged view for recorded signals of data ‘n1_edfm.mat’ from signal 1 to 10.

3.2. Extracting EEG segments from complete data

Out of these data arbitrarily EEG channels segments for feature extraction of sleep disorder are taken. As shown in Fig 3. shows the extracted data for EEG channel 3 from n1_edfm.mat i.e. ROC-LOC in microvolt level (μV).

(a)

(b)

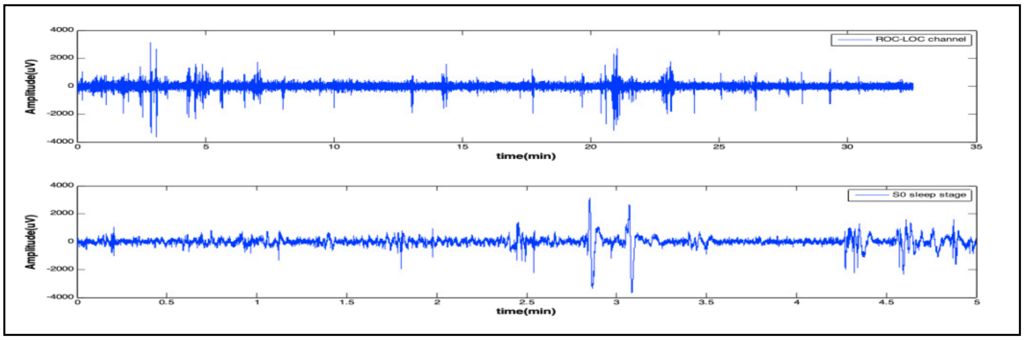

Fig. 3. (a) Voltage Spectrum of Encephalogram of channel ROC–LOC and (b) its segment of the part sleep stage S0.

Fig 3(a). shows a plot of the EEG signal of a normal subject Normal 3 with database name ‘n3_edfm.mat’ it shows the ROC-LOC channel it is the 3rd channel of the given data and in Fig 3(b). It has been shown the clipped signal of duration 5 min consisting of EEG signal of respective channel for sleep stage S0. Here the total signal is of the duration of 30 min, sampling frequency 512Hz, Sleep stage start time is 22:9:33, and end time of S0 is 22:14:33. It can be also extracted in other sleep stage clips by the knowledge of t start and t end of that particular stage. It has been also processed the data of the REM sleep stage. Similarly, it has been taken signals of the subject with

NFLE sleep disorder for S0 and REM. Figure indicates the segmented part of various sleep stages during S0 and REM moments taken from the normal and pathological cases. It can be analysed from these plots that there is variation in magnitude and waveshape patterns of waves in both different cases. Hence normal and pathological cases can express some differences in there features but it cannot be proved directly because EEG signals are multivariable signals and there pattern depends upon mental status of the subject.

3.3. Distortion removal of EEG Signals for Sleep Stages

Now each clipped signal is preprocessed and then passed through a sliding segmentation.

The clipped signal is passed through the segmentation and low-frequency filter for removing the high ripples and distortion components that eventually indicate noise because a major proportion of EEG signals are limited within the range of 25Hz. It indicates a clipped EEG signal for data ‘n1_edfm.mat’ it refers to a normal subject it is a data signal related to the REM stage. It can be analyzed that the enlarged view of the time series plot. shows more details of minute variations or flickers these details are due to high-frequency components since it is being analyzed EEG waves of low-frequency trends. That is why it will be used low frequency-filtered signals as similar is shown in the enlarged view consisting of approximated or a smoothed view of a non-filtered signal. It was enlarged by taking some initial samples (4000 samples) of the total given signal length (460801 samples) of the signal. Because it cannot be visualized minute differences in the plot of signals with a complete no. of samples.

3.4. Filtered and Noisy Electroencephalogram Patterns

The differences in signals after filtering can be measured. Both signals are varying in a similar timeline, but the filtered signal does not contain minute variations in its waveforms. For filtering, it is being used ‘filtfilt’ command that is why there is no phase error in the signal due to phase shifting caused by filter time delay. Since the signal is of a very large length (order of 10^4) but the filter is taken of such a large length, so it is being used filter with a length of segmentation 200. The amplitude response of hanning segmentation that it is being used for filtering of segmentation length of 200 samples. The filter scans 200 samples at a time and allows low-frequency data and filtering out high ripples of each sleep stage. Fig 4. shows the plot of the frequency response of the filter.

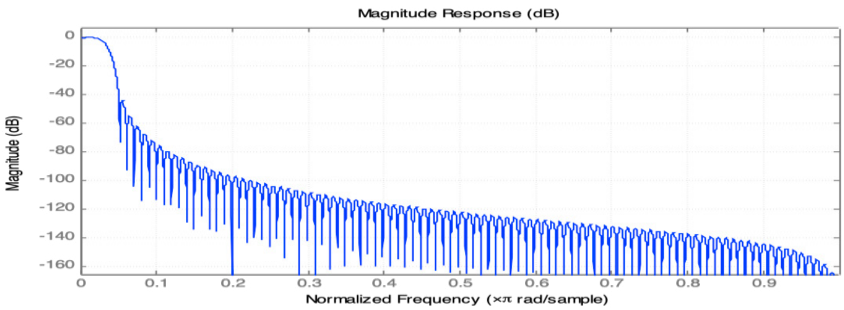

Fig.4. Magnitude (dB) response of FIR filter with low pass feature of cut off frequency 25 Hz.

After applying the filtering each signal is taken to pass through the sliding segmentation to measure the energy level estimation (ELE). The method used for measuring is Welch-Algorithm. Since ELE gives signal energy level estimation with respect to the frequency spectrum, it may require to specify the number of frequency slots to distribute the spectra’s power. It is called as number of FFT points (NFFT). For example the given signal has length of L= 460801 samples then the maximum no. for FFT points are found to be 524288 frequency samples in range of 0 to 25Hz(after low pass FIR filtering) higher no. of FFT points gives more detailed information at small frequency slots. But it is needed only to know energy level estimation in particular frequency band so it is being used only 128 frequency samples for improving performance speed of our program by reducing the computation size Hanning pattern.

3.5. ELE Estimation

After applying the filtering each signal is passed through the sliding segmentation to measure the energy level density (ELE) as shown in Fig 5.

DATA NAME: n1_edfm.mat, Stage: S0

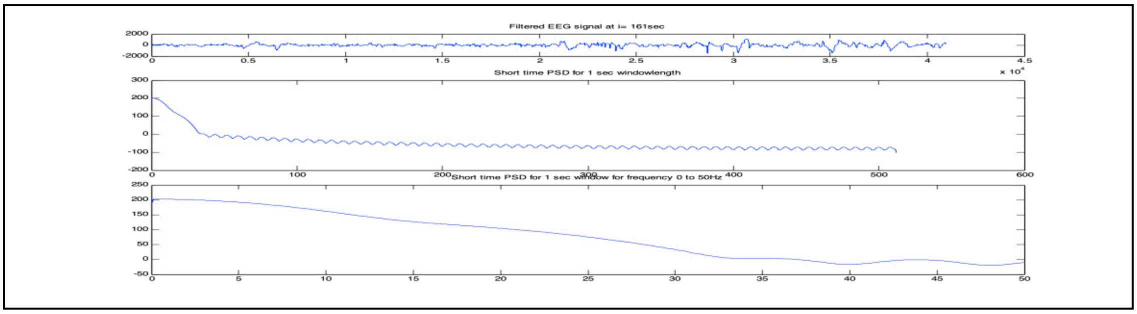

Fig. 5. Short Time ELE of So Stage for NFLE Patient

3.6. Algorithm

In the process of Sleep cycle stage 2, light sleep occurs with very slow eye movements on the onset of getting stop and brain waves signal gradually getting slower. In this stage, sleep spindles are also observed to be started and EEG data value is found average and the range of data frequency exist in between 4 -7 Hz. In the duration observed within occurrence of stage 3 sleep activity moments also known as deep sleep the brain waves rhythms are extremely slow and called as delta waveforms starts to be observed. These waves are interpreted as smaller but faster waveforms. EEG data at this zone of sleep activity possess frequency 1-3 Hz and strength is high. In the sleep cycles of duration occurring in stage 4 also known as deep sleep exhibiting the slow wave the brain initializes the generation of delta waves. In this zone the value of EEG is high and the frequency is below the value of 2Hz. In this stage eye movements are found to be rapid and momentarily muscular moves are associated. Theta wave is common in such sleep stage cycle moments. To better analysis of waveform of REM sleep pattern, it is converted in Power spectrum. For Power conversion by using Welch method. With Welch method, large wave pattern is converted to imbricate. Following three steps used for this, are as under:

(i) Wave pattern is divided in K segments by considering the original wave pattern length as L.
(ii) Window created in step I, enforced to each section
(iii) Take average of K periodograms for wave pattern

$$P_w(e^{j\omega}) = \frac{1}{k}\sum_{k=1}^{K} \quad Px^{(k)}(e^{j\omega}) \;\ldots\ldots\ldots.(1)$$

Where,

$$X_{P_x^{(k)}} = \frac{1}{N}\sum_{n=0}^{L-1} \quad |w_{(n)}x^{(k)}(n)e^{-j\omega n}| \;\ldots\ldots.(2)$$

The above method is applied as per the following phases:

Phase 1: Import EEG data file in the desired format.
Phase 2: EEG data is extracted after downloading 30 to 60 seconds records of sleep movements in different moments of sleep stages of different channels like ROC-LOC, C4-P4 etc.
Phase 3: Removal of mean value, component with zero frequency obtained by FFT algorithm is the mean value of data, which is subtracted from the data to bring all data at similar mean value and bring in the same in range.
Phase 4: After removing the mean value to bring all data in a common range the unwanted frequency and noise is subtracted. This is generally of higher frequency above than the EEG data frequency nearly about 40Hz. For this purpose, files are used that passes low-frequency data and stops high-frequency values, which are generally anomaly in terms of noise, fluctuations, or error. The resultant data after filtering the following benefits:
(i) High-frequency Quency distortion
(ii) only data within EEG frequency level is obtained

Phase 5: Power Calculation, the power estimation is very crucial to figure out the features of data abnormality in defective cases. Welch algorithm is used to calculate the frequency component power by using period gram after applying the Fast Fourier Transform algorithm. The periodogram basically uses the formulae for autocorrelation of fix length of data after clipping or segmenting in equal parts. It gives a simple approach to providing results with very high accuracy.

The periodogram estimate of the frequency components power of fixed length-L of any data segment $x_L[n]$ is

$$P_{xx}(f) = \frac{1}{LF_s}\sum_{n=0}^{L-1} x_{L(n)e^{-j2\pi fn/Fy}} \dots (3)$$

F_s stands for the sampling frequency.

$$f_n = \frac{kF_s}{N} k = 0,1 \dots, N-1 \dots (4)$$

Phase 6: Area covered by plot of power value under the delta, theta, alpha, and gamma frequency range is found through Trapezoidal rule. Theta (θ) frequency 4 to 8Hz, delta (δ) frequency is considered from 0.5 to 4 Hz, alpha (α) frequency range8 to 13 Hz and finally the significant beta (β) wave frequency is considered as 13 to 30 Hz.
Phase 7: After getting the Power under each brain data wave the ratio of these values is intended by isolating the average power of each sleep wave frequency range by the associated average power for complete bands.

4. Result and Discussion

All signals are obtained by performing signal data extraction of the data file named as n1_edfm.mat.It shows the waveform of EEG data records at different channels like voltage data in between ROC and LOC, F2-F4, etc. All the data is in a microvolt and stored in text files. These files are imported to MATLAB and the data is clipped into small parts called segments. Signals indicate the clipped part of various sleep stages during S0 and REM moments taken from the normal and pathological cases. These plots can further be analyzed for the presence of any variation in magnitude and wave shape patterns of waves in both different cases. Hence normal and pathological cases can express some differences in there features but it cannot be proved directly because EEG signals are multivariable signals and there pattern depends upon mental status of the subject.

Table 1. REM stage analysis of NFLE patient EEG data in terms of Energy Level

Type of Wave	Case 1	Case 2	Case 3
Delta Wave	0.5404900	0.5342700	0.6722400
Theta Wave	0.3585900	0.3036400	0.2876500
Alpha Wave	0.0096690	0.0097230	0.0099240
Beta Wave	0.0043856	0.0047566	0.0040866

Energy level of beta wave is lowest in both cases. The percent energy level of delta and theta are high always for both tables (Table 1 - 2). Alpha wave is always in medium level energy value.

Table 2. REM stage analysis of Normal Person EEG data in terms of Energy Level

Type of Wave	Case 1	Case 2	Case 3
Delta Wave	0.7018500	0.4125100	0.5191900
Theta Wave	0.2452100	0.3170500	0.3484200
Alpha Wave	0.0009922	0.0010121	0.0009899

Beta Wave	0.0027850	0.0217140	0.0073007

Table 3. S0 stage analysis of NFLE patient EEG data in terms of Energy Level

Type of Wave	Case 1	Case 2	Case 3
Delta Wave	0.686600	0.548100	0.686600
Theta Wave	0.237700	0.214800	0.237700
Alpha Wave	0.009799	0.009863	0.009954
Beta Wave	0.004500	0.037200	0.004500

Table 3 and 4 are here for the S0 stage pattern analysis of the NFLE disorder and normal person cases. Again, multiple cases are taken here. The energy level on average is observed to be increased in NFLE patients in the alpha wave as compared to the normal person.

Table 4. S0 stage analysis of Normal Person EEG data in terms of Energy Level

Type of Wave	Case 1	Case 2	Case 3
Delta Wave	0.4578000	0.4986000	0.4375000
Theta Wave	0.3435000	0.3603000	0.3126000
Alpha Wave	0.0010123	0.0009932	0.0010389
Beta Wave	0.0074000	0.0055000	0.0054000

As shown in both above tables NFLE sleep disorder can be identified by considering the alpha power spectrum of REM or S0 stage of sleep. In these stages, the percentage energy level is to be high for alpha waves for patients having a sleep disorder. The results show that the average percentage energy level in NFLE patients is 0.009872 while in normal cases it is 0.0010148.
Most of the previous research work related to NFLE sleep disorder was using data sets without smoothening of signals, In this study smoothening of signals is performed for removing the noise from the signal. Thus it can be said that this study will help fellow researchers working in the same domain.

5. Conclusion and Future Scope

In the modern busy world, the impact of stress and a restless lifestyle is of prominence. This has established a culture of small sleep with high depression and anxiety. Due to heavy workloads and challenges at the workplace people are getting disorders in sleep activity and suffering from sleeplessness or inadequate sleep. This article has developed an algorithm to diagnose the sleep disorder of NFLE type using the energy level at different sleep stages under multiple sleep waves. The approach has fussed out the frequency-based classifier strategy to justify the circumstances under which a person is belonging to NFLE sleep disorder. In the future, this approach may be combined with a hybrid of the modern artificial intelligence technique to develop an automated model of diagnosis of other sleep disorders. S0 and REM stages have been found to be crucial to distinguish the NFLE sleep disorder. The average percentage energy level in NFLE patients is 0.009872 while in normal cases it is 0.0010148 during alpha activity. Hence it is concluded that the percentage energy level is increased in NFLE patients in the alpha activity of S0 and REM stages.

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