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PSD Analysis of Neural Spectrum During Transition from Awake Stage to Sleep Stage

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Abstract— **This research paper is intended to provide the analysis of neural waves generated during two stages the awake stage and sleep stage of the particular subject. The 30 second awake signal analysis while subject approaching sleep stage and 30 sec initial sleep stage analysis is considered in the research work.**

I. INTRODUCTION

The brain is the most complex and integral part of human body. The brain comprises of complex network of billions of neurones. These neurones show particular activity at various brain location in different situation. Along with this, neurones network communicates with each other through small electrical signals of around µV. Resultant is the generation of electrical signals. Analysis of these signals can lead us to several conclusions.

II. ELECTROENCEPHALOGRAM(EEG)

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non-invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used in specific applications. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations (popularly called "brain waves") that can be observed in EEG signals.

In EEG system, there is an electrode pair in which one is reference electrode and other electrode measures the voltage fluctuations due to neural oscillations. The research system for the EEG measurement internationally recognized is International 10-20 system.

III. METHOD

Once the EEG signals are obtained they are amplified using differential amplifiers as the signal obtained from the brain are of very low magnitude. Signals are then digitized via analog-to-digital converter using 256-512 Hz with sampling rate up to 20KHz. Further processing of the signals includes the filtering of EEG signals. The EEG signals are then passed through .1Hz low pass filter to 100Hz high pass filter and notch filter to remove the disturbance created by electric power line. The artifacts recorded in the signals are then removed through various other method.

The EEG is typically described in terms of rhythmic activity. The rhythmic activity is divided into bands by frequency. To some degree, these frequency bands are a matter of nomenclature (i.e., any rhythmic activity between 8–12 Hz can be described as "alpha"), but these designations arose because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance. Frequency bands are usually extracted using spectral methods as implemented for instance in freely available EEG software such as EEGLAB. Computational processing of the EEG is often named Quantitative electroencephalography (qEEG). Most of the cerebral signal observed in the scalp EEG falls in the range of 1–20 Hz. Waveforms are subdivided into bandwidths known as alpha, beta, theta, gamma and delta.

TABLE 1
NEURAL WAVE SPECTRUM

Name of the wave	Frequency [Hz]
Delta	0.1 – 4
Theta	4 – 8
Alpha	8 – 13
Beta	13 – 30
Gamma	40 – 80

IV. FOURIER ANALYSIS

A Fourier series decomposes of a periodic signal x(t) in terms of an infinite sum of sines and cosines (or complex exponentials) [14, 6]. Mathematical formula of a Fourier series is presented by following formula (1):

$$x(t) = \frac{a_0}{2} + \sum_{k=1}^{\infty}(a_n \cos(\omega k t) + b_n \sin(\omega k t)), \quad (1).$$

where signal x(t) is integrable on an interval [0, T] and is periodic with period T, t is a time variable, ω is an angular frequency and a_0, a_n, b_n are Fourier coefficients. The expression, angular frequency, is presented as (2):

$$\omega = \frac{2\pi}{T} \quad (2).$$

The Fourier coefficient can be obtained by formulas (3-4):

$$a_n = \frac{2}{T}\int_0^T x(t)\cos(wkt)\,dt,\ k = 0,1,2 \ldots, N \quad (3).$$

$$b_n = \frac{2}{T}\int_0^T x(t)\sin(wkt)\,dt,\ k = 1,2 \ldots, N \quad (4).$$

On the basis of Euler's formula (5):

$$e^{jt} = cost + jsint, \quad (5).$$

Fourier series can be also presented as (6):

$$x(t) = \sum_{k=-\infty}^{k=\infty} c_n . e^{j\omega kt} \quad (6).$$

where coefficient n c is obtained as (7):

$$c_n = \frac{1}{T}\int_0^T x(t)\, e^{-j\omega kt} dt \quad (7).$$

A generalization of Fourier series, for infinite domains, is Continuous Fourier Transform (CFT). CFT is used to transform signals between time domain and frequency domain. The term CFT is presented as (8):

$$F(\xi) = \int_{-\infty}^{\infty} x(t)\, e^{-2\pi tj\xi} dt \quad (8).$$

Then the inverse CFT (to transform signals between frequency domain and time domain) can be written as (9):

$$x(t) = \int_{-\infty}^{\infty} F(\xi)\, e^{-2\pi tj\xi} d\xi \quad (9).$$

If the signal is periodic, band-limited and sampled at Nyquist frequency or higher, the CFT is represented exactly by Discrete Fourier Transform (DFT). DFT transforms the sequence of N complex numbers $x_0, x_{1,\ldots\ldots,} x_{N-1}$ (the time domain) into an N-periodic sequence $X_0, X_{1,} \ldots, X_{N-1}$ (the list of coefficient of a finite combination of complex sinusoids, ordered by their frequencies). It is according to the DFT formula [10] (10):

$$X_k = \sum_{n=0}^{N-1} x_n\, e^{-2\pi jkn/N} \quad (10).$$

Each $X_k$element encodes amplitude and phase of a sinusoidal component of function x_n. Inverse conversion to the DFT is the Inverse DFT (IDFT). The IDFT transforms data from the frequency domain to the time domain. It is according to the IDFT formula (11):

$$x_n = \frac{1}{N}\sum_{k=0}^{N-1} X_k\, e^{2\pi jkn/N} \quad (11).$$

In this paper, A Fast Fourier Transform (FFT) is used as efficient algorithm to compute the DFT and its inverse (IFFT to compute IDFT) [1, 2]. Computational complexity is $O(N^2)$ for standard DFT and N(log N) for FFT procedure. FFT algorithm is based on Divide and Conquer algorithm. It divides the transform of size N to transform the size N_1 and N_2 . In this paper, the FFT algorithm is using for size of sample, according formula (12):

$$N = 2^k \quad (12).$$

where *k* is a natural number.

V. Power Spectral analysis

The goal of spectral estimation is to describe the distribution (over frequency) of the power contained in a signal, based on a finite set of data. Estimation of power spectra is useful in a variety of applications, including the detection of signals buried in wideband noise.

The power spectral density (PSD) of a stationary random process x(n) is mathematically related to the autocorrelation sequence by the discrete-time Fourier transform. In terms of normalized frequency, this is given by (13):

$$P_{xx}(\omega) = \frac{1}{2\pi}\sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-j\omega m} \quad (13).$$

This can be written as a function of physical frequency f (e.g., in hertz) by using the relation ω = 2πf / fs, where fs is the sampling frequency (14):

$$P_{xx}(f) = \frac{1}{f_s}\sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-j2\pi mf/f_s} \quad (14).$$

The correlation sequence can be derived from the PSD by use of the inverse discrete-time Fourier transform (15):

$$R_{xx}(m) = \int_{-\pi}^{\pi} P_{xx}(\omega) e^{jwn} d\omega = \int_{-f_{s/2}}^{f_{s/2}} P_{xx}(f) e^{j2\pi mf/f_s} df \quad (15).$$

The average power of the sequence x(n) over the entire Nyquist interval is represented by (16):

$$R_{xx}(0) = \int_{-\pi}^{\pi} P_{xx}(\omega) d\omega = \int_{-f_{s/2}}^{f_{s/2}} P_{xx}(f) df \quad (16).$$

The average power of a signal over a particular frequency band [ω1, ω2], 0 ≤ ω1 ≤ ω2 ≤ π, can be found by integrating the PSD over that band (17):

$$P_{[\omega_1,\omega_2]} = \int_{\omega_1}^{\omega_2} P_{xx}(\omega) d\omega = \int_{-\omega_2}^{-\omega_1} P_{xx}(\omega) d\omega \quad (17).$$

We can see from the above expression that Pxx(ω) represents the power content of a signal in an infinitesimal frequency band, which is why it is called the power spectral density.

The units of the PSD are power (e.g., watts) per unit of frequency. In the case of Pxx(ω), this is watts/radian/sample or simply watts/radian. In the case of Pxx(f), the units are watts/hertz. Integration of the PSD with respect to frequency yields units of watts, as expected for the average power.

For real–valued signals, the PSD is symmetric about DC, and thus Pxx(ω) for 0 ≤ ω ≤ π is sufficient to completely characterize the PSD. However, to obtain the average power over the entire Nyquist interval, it is necessary to introduce the concept of the one-sided PSD.

The one-sided PSD is given by (18):

$$P_{one-sided}(\omega) = \begin{cases} 0, & -\pi \le \omega < 0, \\ 2P_{xx}(\omega), & 0 \le \omega \le \pi. \end{cases} \quad (18).$$

The average power of a signal over the frequency band, [ω1,ω2] with 0 ≤ ω1 ≤ ω2 ≤ π, can be computed using the one-sided PSD as (19):

$$P_{[\omega_1,\omega_2]} = \int_{\omega_1}^{\omega_2} P_{one-sided}(\omega) d\omega \quad (19).$$

VI. EXPERIMENT AND RESULTS

The readings taken at same time, from various electrodes of EEG system were summed up to observe the overall distribution of spectral power. The research was conducted on the overall power distribution.

The analysis of two samples from two subject each sample of transition from awake stage to initial sleep stage was done. PSD during 30 seconds before sleep stage (Awake Stage) and 30 second after sleep stage (Sleep Stage) are compared. Fig. 1 and Fig. 2 shows the signal and PSD of Awake Stage for subject 1 sample 1. Fig. 3 and Fig. 4 shows the signal and PSD of Sleep Stage for subject 1 sample 1. Fig. 5 and Fig. 6 shows the signal and PSD of Awake Stage for subject 1 sample 2. Fig. 7 and Fig. 8 shows the signal and PSD of Sleep Stage for subject 1 sample 2. Fig. 9 and Fig. 10 shows the signal and PSD of Awake Stage for subject 2 sample 1. Fig. 11 and Fig. 12 shows the signal and PSD of Sleep Stage for subject 2 sample 1. Fig. 13 and Fig. 14 shows the signal and PSD of Awake Stage for subject 2 sample 2. Fig. 15 and Fig. 16 shows the signal and PSD of Sleep Stage for subject 2 sample 2.

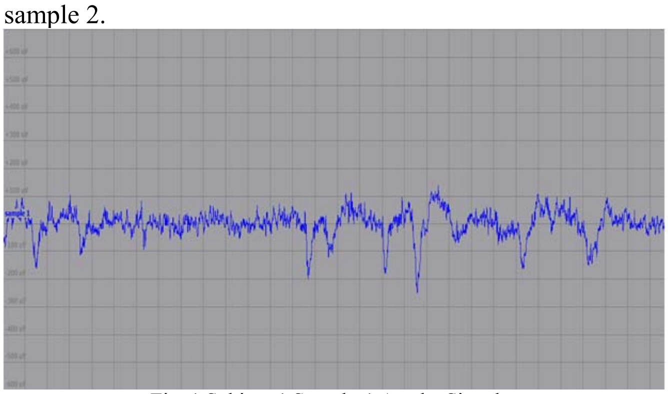

Fig. 1 Subject-1 Sample-1 Awake Signal

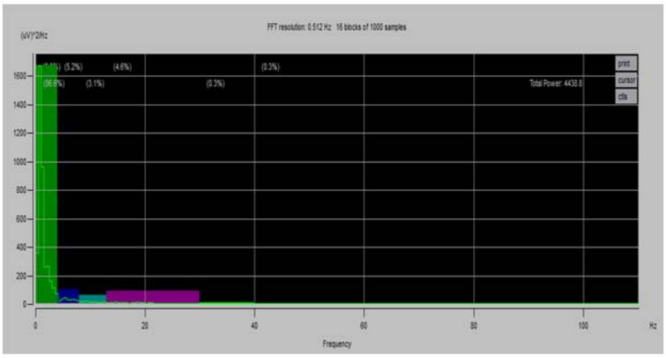

Fig. 2 Subject-1 Sample-1 Awake PSD

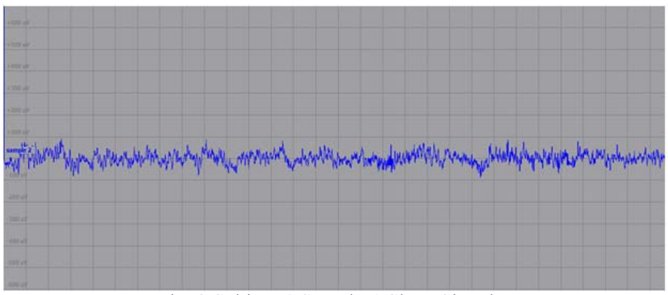

Fig. 3 Subject-1 Sample-1 Sleep Signal

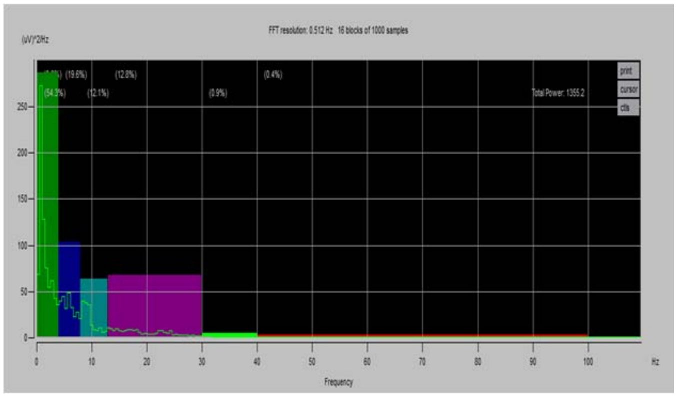

Fig. 4 Subject-1 Sample-1 Sleep PSD

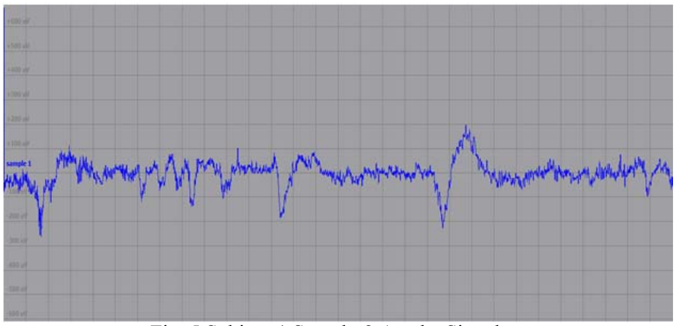

Fig. 5 Subject-1 Sample-2 Awake Signal

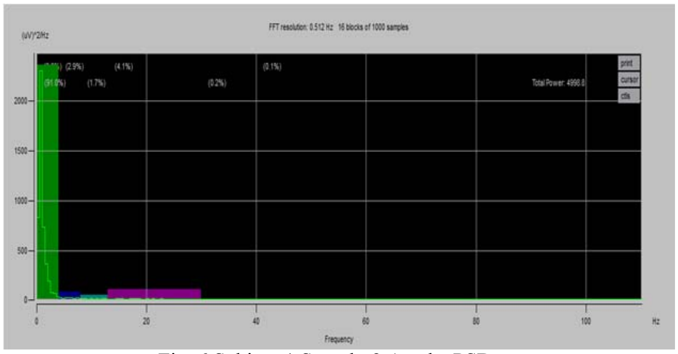

Fig. 6 Subject-1 Sample-2 Awake PSD

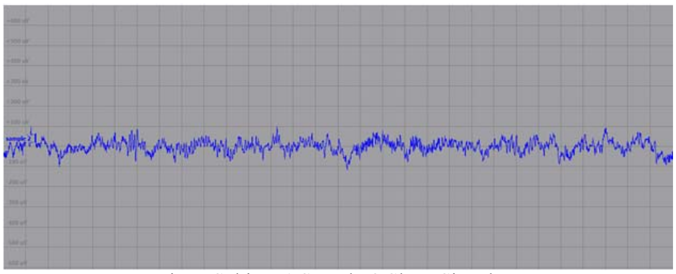

Fig. 7 Subject-1 Sample-2 Sleep Signal

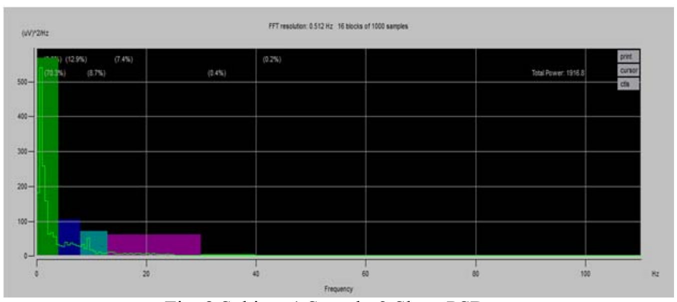

Fig. 8 Subject-1 Sample-2 Sleep PSD

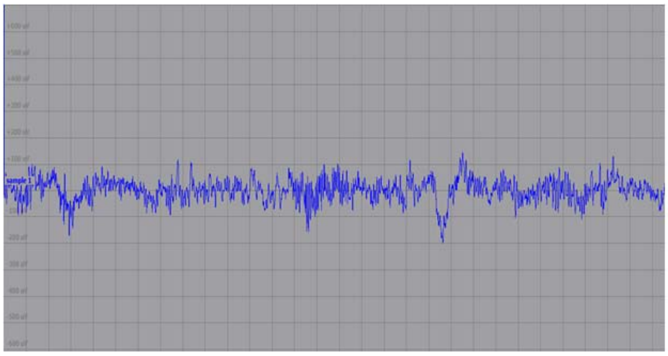

Fig. 9 Subject-2 Sample-1 Awake Signal

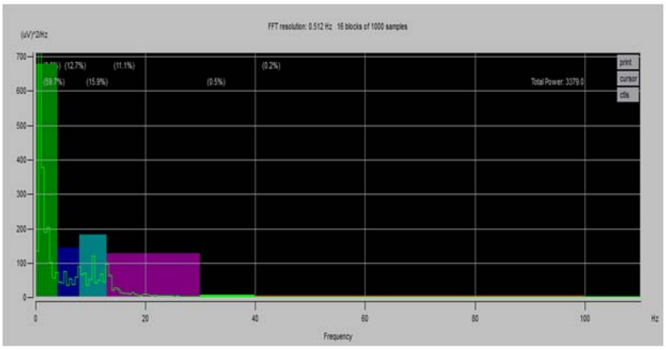

Fig. 10 Subject-2 Sample-1 Awake PSD

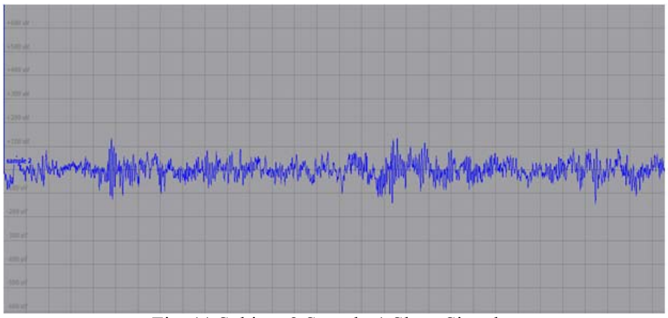

Fig. 11 Subject-2 Sample-1 Sleep Signal

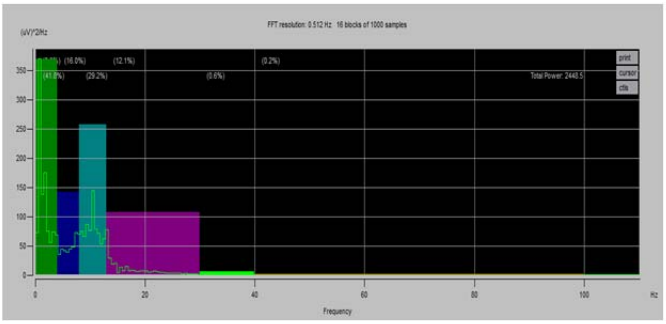

Fig. 12 Subject-2 Sample-1 Sleep PSD

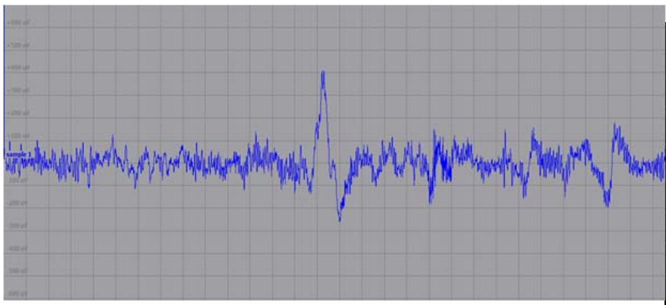

Fig. 13 Subject-2 Sample-2 Awake Signal

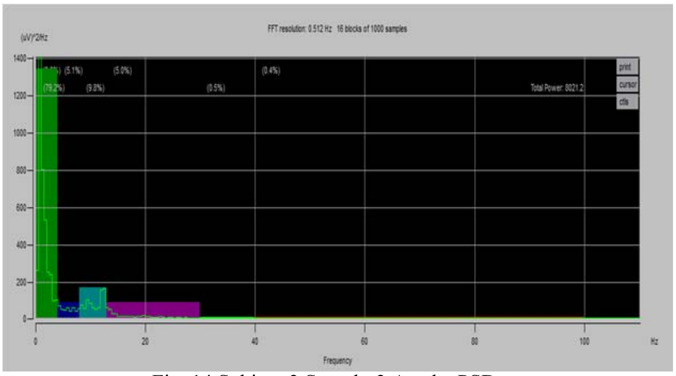

Fig. 14 Subject-2 Sample-2 Awake PSD

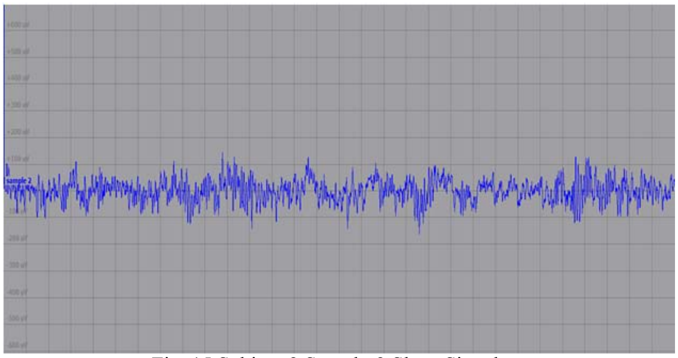

Fig. 15 Subject-2 Sample-2 Sleep Signal

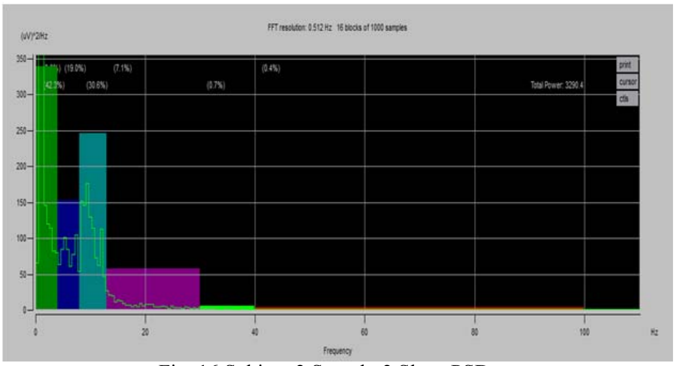

Fig. 16 Subject-2 Sample-2 Sleep PSD

The results were analysed and a classification was made for each sample from the subjects. The below table shows the total power spectral density, percentage and original values of contribution of each spectrum during awake and sleep stage. Table I (Sample 1) and Table II (Sample 2) are for subject 1. Table III (Sample 1) and IV (Sample 2) are for subject 2.

TABLE I
SUBJECT 1 SAMPLE 1 AWAKE SLEEP POWER DISTRIBUTION ACCORDING TO SPECTRUM

Total Power →	**Awake**	**4438.8**	**Sleep**	**1355.2**
	Percentage		**Power Distribution**	
Spectrum↓	**Awake**	**Sleep**	**Awake**	**Sleep**
Delta	86.6	38.7	3844.0008	524.4624
Theta	5.2	19.1	230.8176	258.8432
Alpha	3.1	26.8	137.6028	363.1936
Beta	4.6	14.4	204.1848	195.1488
Gamma	0.3	0.3	13.3164	4.0656

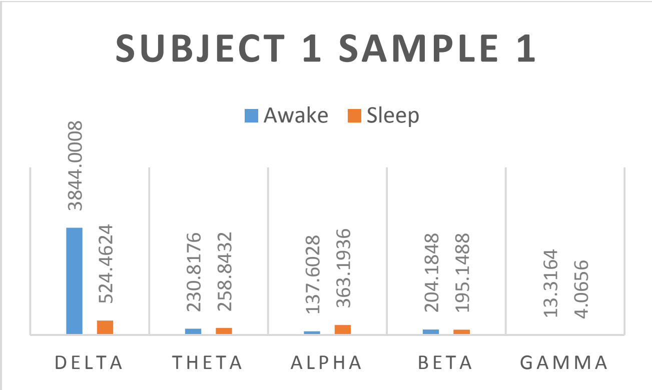

Fig.17 PSD of Spectrums in Sleep and Awake stage of sample 1 subject 1

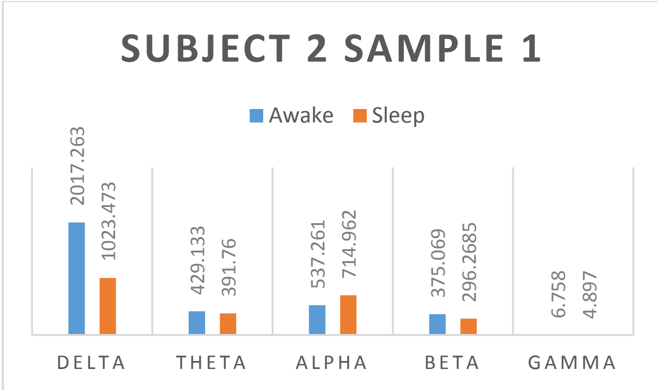

Fig.17 PSD of all Spectrums in Sleep and Awake stage of sample 1 subject 2

TABLE II
SUBJECT 1 SAMPLE 2 AWAKE SLEEP POWER DISTRIBUTION ACCORDING TO SPECTRUM

Total Power →	**Awake**	**4998.8**	**Sleep**	**1916.8**
	Percentage		**Power Distribution**	
Spectrum↓	**Awake**		**Awake**	**Sleep**
Delta	91	70.3	4548.908	1347.5104
Theta	2.9	12.9	144.9652	247.2672
Alpha	1.7	8.7	84.9796	166.7616
Beta	4.1	7.4	204.9508	141.8432
Gamma	0.1	0.2	4.9988	3.8336

TABLE IV
SUBJECT 2 SAMPLE 2 AWAKE SLEEP POWER DISTRIBUTION ACCORDING TO SPECTRUM

Total Power →	**Awake**	**8021.2**	**Sleep**	**3290.4**
	Percentage		**Power Distribution**	
Spectrum↓	**Awake**	**Sleep**	**Awake**	**Sleep**
Delta	79.2	42.3	6352.79	1391.8392
Theta	5.1	19	409.081	625.176
Alpha	9.8	30.6	786.07	1006.8624
Beta	5	7.1	401.06	233.6184
Gamma	0.4	0.4	32.0848	13.1616

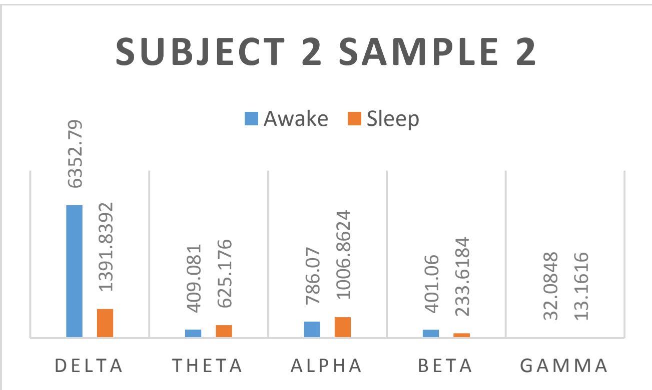

Fig.17 PSD of Spectrums in Sleep and Awake stage of sample 2 subject 1

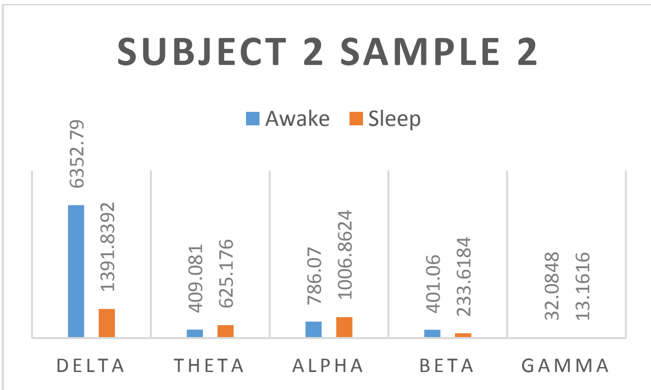

Fig.17 PSD of all Spectrums in Sleep and Awake stage of sample 2 subject 2

TABLE III
SUBJECT 2 SAMPLE 1 AWAKE SLEEP POWER DISTRIBUTION ACCORDING TO SPECTRUM

Total Power →	**Awake**	**3379**	**Sleep**	**2448.5**
	Percentage		**Power Distribution**	
spectrum↓	**Awake**	**Sleep**	**Awake**	**Sleep**
Delta	59.7	41.8	2017.263	1023.473
Theta	12.7	16	429.133	391.76
Alpha	15.9	29.2	537.261	714.962
Beta	11.1	12.1	375.069	296.2685
Gamma	0.2	0.2	6.758	4.897

Through above mentioned reading it can be deduced that during sleep stage power of alpha waves increases whereas the power of Delta, Beta and Gamma waves reduces.

VII. CONCLUSIONS

This paper presents the method of processing and observation of neural signals. The Fourier analysis and Power Spectral Density has always been an efficient way for observing various spectrum. During this research two sample each of combined 60 seconds during awake to sleep stage transition was considered. After that each sample was compared with each other to draw the conclusion.

In the result, it was observed that during awake stage Alpha waves contributed low magnitude in total power where as in sleep stage Alpha waves had major contribution, even more than that during awake stage. Whereas the contribution of Delta, Beta and Gamma waves were reduced during the Sleep Stage compared to Awake Stage. These observations could be useful to the system engaged in detection of transition of a human being from awake stage to sleep stage.

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