Feature Extraction of Human Sleep EEG Signals using Wavelet Transform and Fourier Transform

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Abstract— **Electroencephalogram (EEG) is a complex signal resulting from postsynaptic potentials of cortical pyramidal cells and an important brain state indicator with specific state dependent features. Modern brain research is intimately linked to the feasibility to record the EEG and to its quantitative analysis. EEG spectral analysis is an important method to investigate the hidden properties and hence the brain activities. Spectral analysis of sleep EEG signal provides acute insight into the features of different stages of sleep which can be utilized to differentiate between normal and pathological conditions. This paper describes the process of extracting features of human sleep EEG signals through the use of multi resolution Discrete Wavelet Transform and Fast Fourier Transform. Discrete Wavelet Transform offers representations of the signals in the time-frequency plane giving information regarding the time localization of the spectral components at different stages of sleep in human beings and Fast Fourier Transform provides the spectral information. This paper also discusses the clinical correlation associated with sleep EEG signals in brief.**

Keywords-Electroencephalogram (EEG); Wavelet Transform, Fast Fourier Transform.

I. INTRODUCTION

The EEG (Electroencephalogram) signal indicates the electrical activity of the brain. The electrical activity of a brain (EEG) exhibits significant complex behavior with strong non-linear, random and non-stationary properties. The communication in the brain cells take place through electrical impulses. It is measured by placing the electrodes on the scalp of the subject. The cortical nerve cell inhibitory and excitatory postsynaptic potentials generate the EEG signals. These postsynaptic potentials summate in the cortex and extend to the scalp surface where they are recorded as EEG. A typical EEG signal, measured from the scalp, will have amplitude of about 10 μV to 100 μV and a frequency roughly in the range of 0.25 Hz to about 100 Hz [1]. EEG, as a noninvasive testing method, plays a key role in diagnosing diseases and is useful for both physiological research and medical application. It helps in diagnosing many neurological diseases, such as epilepsy, tumor, cerebrovascular lesions, breathing disorders associated with sleep, depressions and problems associated with trauma. EEG traces are different for different brain activities. The brain activity of an abnormal person can easily be distinguished from a normal person by matching the features of the EEG waves. There are various events, namely: sleep, epilepsy, reflexology, drugs/anesthesia, diabetes, meditation, music and artifacts influence the EEG signal. However, it is very difficult to get useful information from these signals directly in the time domain just by observing them. EEG signals are highly non-Gaussian, non-stationary and have a non-linear nature. Hence, important features can be extracted for the diagnosis of different diseases using advanced signal processing techniques. A number of signal of signal processing techniques are available for the analysis of EEG signals (like- Fast Fourier Transform, S Transform, Wavelet Transform etc.). The objective of this paper is to analyze features of human sleep EEG signals using Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT). These characteristics features can be used to identify any disorder and thus can play important roles in diagnosing disorders and pathological conditions.

II. SLEEP STRUCTURE AND STATES

Sleep EEG signals contain four spectral bands of clinical interest. These are the δ band (1.3 -3.5 Hz), θ band (3.5 – 7.5 Hz), α band (7.5 – 13 Hz) and β band (13 – 35 Hz). Sleep is generally divided into two broad types: non rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. Based on EEG changes, NREM is divided further into four stages (i.e. stage I, stage II, stage III, and

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stage IV). NREM and REM occur in alternating cycles, the sequence being stage I, Stage II, stage III, stage IV, REM and begins again with stage I. When brain is awake and busy, the brain waves are desynchronized and very much irregular. When relaxed, brain generates waves in α- band. As the brain enters the sleep stages, the brain waves become progressively slower and grow in amplitude. Fig.1 represents the sleep cycles. The cycle starts with stage I and ends with REM sleep. Each of the stages last around 12 – 15 minutes with the whole cycle takes about 90-120 minutes. [1-2]

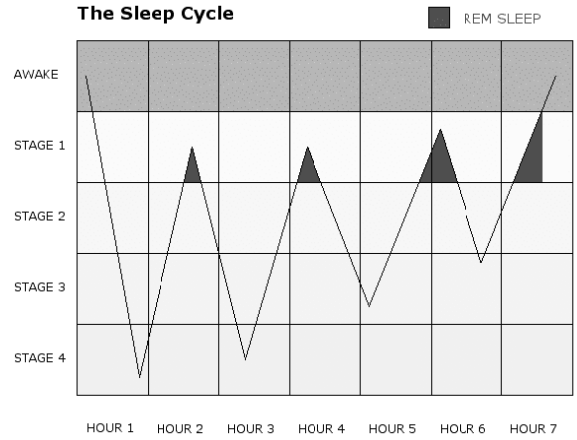

Figure.1 The complete sleep cycle

A. Stage I sleep

First indication of stage I sleep is the slow rolling eye movements (SREMs). Their distribution is quite similar to eye movements in general (considered as EEG Artifact). However, SERMs are slower (i.e. typically 0.25-0.5 Hz). SREMs disappear in the consequent deeper sleep stages. Generally SERMs are accompanied by attenuation of the alpha rhythm (alpha activity). The alpha activity gradually becomes slower, less prominent, and fragmented. The other prominent signs of stage I sleep are central or frontocentral theta activity, enhanced beta activity, Positive occipital sharp transients of sleep (POSTS), and Vertex sharp transients. POSTS amplitude varies in the range of 50-100 μV and they occur in 4-5 Hz range. Vertex sharp transients (v waves) like K complexes of stage II sleep, vertex waves are maximal at the vertex, usually appear symmetrically. Their amplitude is 50-150 μV, can be contoured sharply and occur in repetitive runs. They persist in stage II sleep but usually disappear in subsequent stages. Unlike K complexes, vertex waves are narrower and more focal. [1]

B. Stage II sleep

The distinct and prominent features of stage II sleep is the appearance of sleep spindles and K complexes. The presence of sleep spindles is necessary and sufficient to define stage II sleep. Sleep spindles have a frequency of 12-16 Hz (typically 14 Hz) and are maximal in the central region (vertex), although they are occasionally predominant in the frontal regions. Amplitude is usually 20-100 μV although extreme spindles can have amplitudes as high as 100-400 μV. K complexes which are associated with the sleep spindles are also an important characteristics of stage II sleep. K complexes are high in amplitude (>100 μV), broad (>200 ms), located in frontocentral region, with a typical maximum at the midline. Except for slow rolling eye movements, all features of stage I sleep persist in stage II sleep. The prominent patterns of stage II sleep, spindles and K complexes are usually easy to identify and thus are less prone to misinterpretation than the patterns of stage I sleep.

C. Stage III and Stage IV Sleep

Stages III and IV sleep are usually known as "slow wave sleep" or "delta sleep." SWS or delta sleep is characterized by delta activity and relative body immobility. Generally SWS is defined by the presence of such delta activity for more than 20% of the time with an amplitude level of at least 75 μV. the amount of delta activity separates stage III sleep from stage IV sleep. Stage III is defined by delta activity that occupies 20-50% of the time, whereas in stage IV, delta activity represents greater than 50% of the time. Sleep spindles and K complexes may persist in stage III and even to some degree in stage IV, but they are not prominent.

D. REM sleep

REM sleep is characterized by rapid eye movements, muscle atonia, and EEG desynchronization (compared to slow wave sleep). In addition REM sleep can also be identified by the appearance of saw tooth wave in the EEG recordings. The duration of REM sleep increases progressively with each cycle and tends to predominate late in the sleep period. The occurrence of REM too soon after sleep onset, referred to as SOREMP, is considered pathological. [1-2]

Table I. summarizes the characteristics of all the sleep stages with dominant spectral components, amplitude of the waves and nature of the waves.

TABLE I. SUMMARY OF ALL THE SLEEP STAGES

Stage	Frequency (Hz)	Amplitude	Waveform type
Awake	15 – 50	< 50	Desynchronized EEG
Pre-sleep	8 – 12	50	Alpha waves
Stage I	4 – 8	50 – 100	Theta waves
Stage II	4 – 15	50 – 150	Sleep spindles and K Complexes
Stage III	2 – 4	100 – 150	Sleep spindles and delta waves
Stage IV	0.5 – 2	100 – 200	Delta waves
REM	15 – 30	< 50	Desynchronized EEG with low amplitudes and high frequencies.

III. MULTI-RESOLUTION ANALYSIS AND WAVELET TRANSFORM

While analyzing the EEG signals, it is not always sufficient to have the information about spectral component. Sometimes the time localization of these spectral components also plays an important part in the analysis. Multi-resolution analysis provides the required time and frequency information by varying the resolution properties for different spectral components. Wavelet transform is a multi resolution analysis method. It possesses localization features both in time and frequency domain. Wavelet transform forms a general mathematical tool 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. [3-6]

A. Continuous Wavelet Transform

The Continuous Wavelet Transform (CWT) is described by the following equation,

$$X_{\omega}(\tau, s)=\frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} x(t)\psi * (\frac{t-\tau}{s})dt$$

Where x (t) is the signal to be analyzed, ψ (t) is the mother wavelet or the basis function, s is the scale parameter and τ is the translation parameter. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression). The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter s is defined as |1/frequency| and corresponds to frequency information. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide global information about the signal, while small scales (high frequencies) compress the signal and provide detailed information hidden in the signal. [3-6]

B. Discrete Wavelet transform

The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of wavelet transform. It is easy to implement and reduces the computation time and resources required. The DWT of a sequence x[n] is calculated by passing it through a series of half band high pass and low pass filters. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations and the scale is determined by upsampling and downsampling operations. [3]First the samples are passed through a low pass filter with impulse response g[n] and a high pass filter with impulse response h[n]. The output is the convolution of the two:

$$y_{low}[n] = x[n] * g[n] = \sum_{k=-\infty}^{\infty} \mathrm{x[k].g[n-k]}$$

$$y_{high}[n] = x[n] * h[n] = \sum_{k=-\infty}^{\infty} \mathrm{x[k].h[n-k]}$$

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then downsampled by 2. The filter outputs are then given by

$$y_{low}[n] = x[n] * g[n] = \sum_{k=-\infty}^{\infty} \mathrm{x[k].g[2n-k]}$$

$$y_{high}[n] = x[n] * h[n] = \sum_{k=-\infty}^{\infty} \mathrm{x[k].h[2n+1-k]}$$

Passing the input sequence through the half band filters once form one level of decomposition coefficients. Subsequent levels of decomposition can be by cascading such filter banks with each level of filter banks corresponds to that particular level of decomposition. Fig.2 shows three level DWT of the input signal which is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by g[n] while the high pass filter is denoted by h[n]. At each level, the high pass filter produces detail information, while the low pass filter associated with scaling function produces coarse approximations.

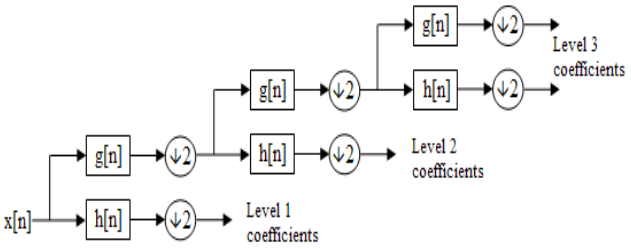

Figure.2 Three level DWT of the input signal x[n]

DWT along with Fast Fourier Transform (FFT) can be a powerful tool for decomposing and spectral analysis of biomedical signals (like EEG signals).

IV. EEG DATA AND PRACTICAL ANALYSIS

The sleep EEG recordings were obtained from Sleep EDF database under PhysioBank archives maintained by Massachusetts Institute of Technology (MIT), which is a physiological signal archive for biomedical research. PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community. The EEG signals were obtained from 8 healthy subjects both males and females aged between 21 - 35 years without any medication contained FpzCz and PzOz EEG. The length of each data record is 1 hour, and each sampled at 100 Hz (i.e. 360000samples) [7]. Practical analysis is composed of two

main processes: (a) filtering of EEG data, and (2) decomposition of the filtered EEG signals.

A. EEG Data Filtering

The EEG data were filtered using 4th order band pass Elliptic filter. The pass band frequencies were set from (2-to-40) Hz. The filtered signals have only EEG waves (delta, theta, alpha, and beta) with all the undesired frequency components removed, as the main characteristic features of different stages of the sleep lies in these low frequencies.

B. Decomposition of Filtered EEG Data

The analysis at any time within the period of each of the sleep stages in the cycle should yield the specific characteristics associated with that particular sleep stage. In this paper, the sleep EEG signals were analyzed for each of the sleep stages with the help of Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT). DWT is used to decompose the EEG waves into detailed coefficient and later on the FFT is applied on the coefficients of each of decomposition levels. The result of the FFT operation will reveal the major frequency components at each of the decomposition levels. The characteristics obtained from this analysis almost conforms the desired ones.

C. Analysis of EEG Data

Fig.3 is obtained by applying FFT to the level 4 and level 5 coefficients of the decomposition. From the FFT plot of level 4 coefficients in Fig.3, it can be observed that the major frequency components are around 2.5 - 8 Hz, which accounts for the theta waves. The spectral components around 0 - 0.5 Hz indicates the presence of slow rolling eye movements. The other notable phenomenon is the lack of alpha activity denoted by the absence of spectral components around 9 – 12 Hz. These events are enough to characterize stage I sleep.

Fig.4 is the FFT plot of the level4 and level 5 coefficients of this signal between 25-30 minutes from the start of the EEG recording. It can be observed, that except the slow rolling eye movements, the other features of stage I sleep are still prevailing and the increase activity around 15 Hz accounts for the sleep spindles.

Fig.5 represents the sleep EEG signal of the subject after 30 minutes of the start of the recording. The subject's EEG signal is marked by sleep spindles which are the stigmata of stage II sleep. Fig.6 shows the k-complexes.

Fig.7 shows the frequency spectrum of the level 4 and level 5 decomposition coefficients. The spectrum indicates the increase in delta activity which characterizes the stage III and stage IV sleep.

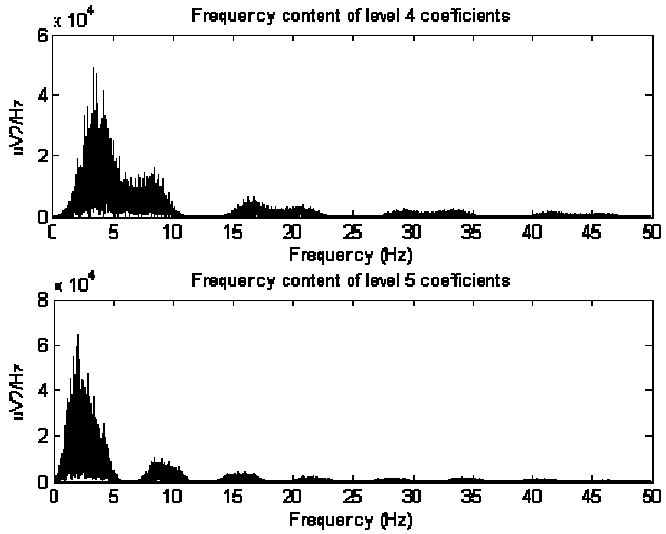

Figure.3 Frequency spectrum of level 4 and level 5 decomposition coefficients within the time ranging from 5-15minutes from the start of the EEG recording.

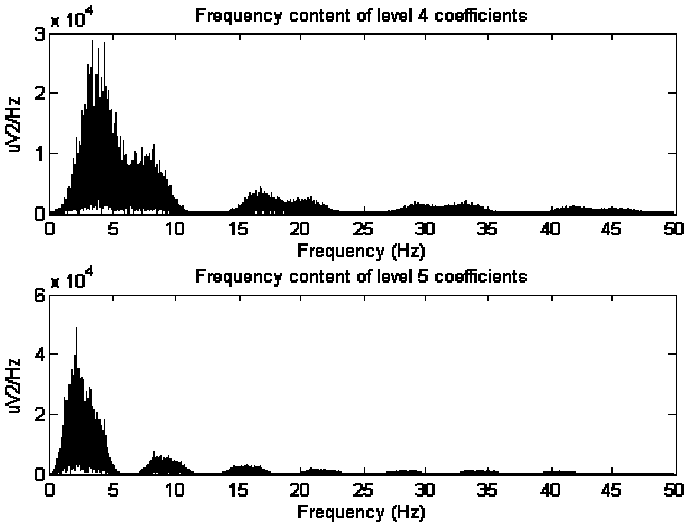

Figure.4 Frequency spectrum of level 4 and level 5 decomposition coefficients within the time ranging from 25-30minutes from the start of the EEG recording.

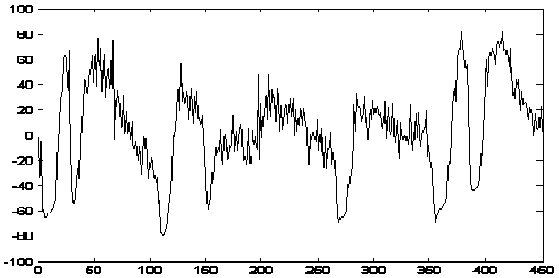

Figure.5 Sleep spindles in EEG waveform.

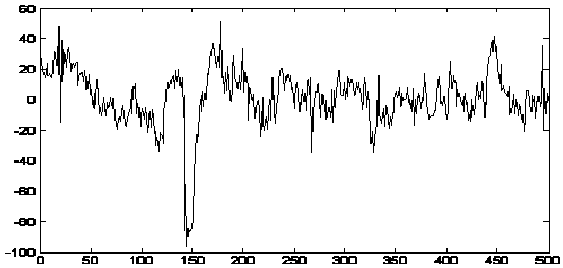

Figure.6 K-complex in Stage II EEG waveform

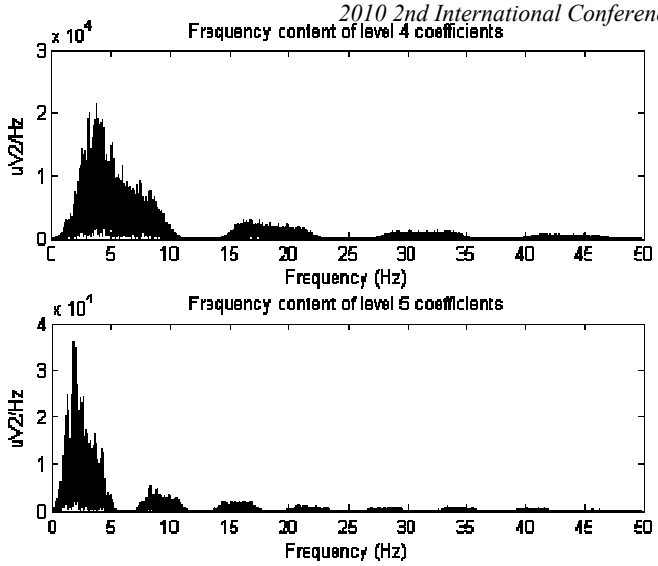

Figure.7 Frequency spectrum of level 4 and level 5 decomposition coefficients within the time ranging from 45-55 minutes from the start of the EEG recording.

From the above analysis results, it is very much evident that both the time and frequency information can be retrieved using the combination of DWT and FFT. This allows the analysis to be done in much more flexible way and more useful information (like what spectral components persist at what instants of time) can be retrieved. This information is more likely to lead to more accurate analysis and diagnosis of abnormalities and pathological conditions.

V. CLINICAL CORRELATION

The sleep EEG signals can be used to identify disorders and abnormalities. The healthy sleep EEG patterns are matched with the patterns under scrutiny and can be analyzed for abnormalities. Various kinds of neurological diseases can be identified with the help of EEG signals. Sleep disorders, sleep apnea, mental distress, epilepsy, tumors, cerebrovascular and other brain lesions etc. are a few prominent names. Significant research activities are going around the world to develop these techniques. With the improvement of the biomedical signal acquisition tools and signal processing techniques, it is likely that the effectiveness and accuracy of this kind of analysis will grow up by manifolds.

VI. CONCLUSION

Biomedical signal processing is one of the flourishing areas of modern science and engineering with EEG signal processing is one of the very important facets of this area. Tremendous research and development activities are going around the world. Medical science in collaboration with modern engineering techniques can provide a massive amount of useful information and solutions in this field. Signal processing techniques are part and parcel of EEG analysis. This paper used the technique of Discrete Wavelet Transform and Fast Fourier Transform to characterize the various stages associated with human sleep. This technique can be useful in extracting features of the sleep EEG signals at a very low cost with the aid of computers. The accuracy of this technique is likely to be raised with the improvement of the biomedical signal acquisition tools, with the development of digital filters and of course with the development of more accurate signal processing algorithms.

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