DETECTION OF SLEEP DISORDERED BREATHING

USING ELECTROENCEPHALOGRAPHY

by

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ABSTRACT

DETECTION OF SLEEP DISORDERED BREATHING

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This study investigates the application of Electroencephalography (EEG) to detect Sleep disordered breathing (SDB) using power spectral analysis. A preliminary study was performed on 13 subjects (ages: 49.08 ± 8.82) previously diagnosed with OSA. Power spectral analysis was performed and centered on apnea/hypopnea event terminations. The normalized power changes between the frequency bands delta, theta, alpha and sigma were calculated using the Welch Averaging Periodogram method between 10 s of EEG data before the event termination and 10 s of EEG data after event termination. A significant decrease in normalized delta power and a significant increase in normalized theta, alpha and sigma power were observed across the event terminations. The values of the differences in the normalized powers were studied and

threshold values corresponding to changes in delta, theta, alpha and sigma bands were chosen. Differences in normalized powers equal to or greater than these thresholds were hypothesized to indicate the presence of event terminations. Power spectral changes were calculated across the EEG signal for the entire night duration by the application of two adjacent 10 s sliding windows moved 5s at a time. Normalized power differences across the sliding windows corresponding to values greater than the threshold values of delta and threshold values of either theta/alpha/sigma were scored as event terminations. These detections were then verified with the EEG signal which had been previously scored by a sleep specialist from an accredited sleep lab and who was blind to the objective of this study. The results showed a good correlation (r=0.98) but a number of detections not corresponding to apneic/hypopneic events were observed in both OSA and Control group. These are hypothesized to be due to other cortical activity like RERA's (Respiratory effort-related arousal), transient arousals or K-complexes/spindles which have similar characteristics to cortical arousals. In conclusion, this method proved to be successful in detecting apneic/ hypopneic events but cannot be used as a method to diagnose SDB without further investigation.

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CHAPTER 1

INTRODUCTION

1.1 Sleep-Disordered Breathing

Sleep is a physiological process which performs restorative functions for the brain and the body. It is necessary in order to maintain a healthy status for most living organisms. The myriad of metabolic dysfunctions that are symptoms of deficiency of sleep are a witness to this important fact. A recent finding shows that one third of the human population suffers from various sleep disorders which could be due to the contemporary life style, increased exposure to stress, decreased physical activity or due to the increasing spread of obesity [1]. It is estimated that millions of Americans suffer from sleep apnea but are undiagnosed. The need to alleviate the problems of cost-effectiveness and constraints on bed space in sleep laboratories remain. There is also a demand for methods and standardization of criteria for diagnosis in order to conduct unattended home monitoring [2].Studies have shown that there are changes in cortical activity that occur during sleep disordered breathing (SDB) events. In order to take advantage of this attribute to devise a more economical method to detect sleep-disordered breathing events, this investigation focused on the sole ability of cortical electroencephalography to detect sleep-disordered breathing events.

1.2 Obstructive Sleep Apnea (OSA): Definition and Pathophysiology

Sleep Disordered Breathing (SDB) is a general term applicable to a wide variety of sleep-related breathing disorders that are characterized by repeated pauses in breathing leading to fragmentation of sleep and decreases in oxyhemoglobin saturation accompanied by hypercapnia [3].

Sleep apnea is a common sleep disorder characterized by brief interruptions of breathing during sleep. The most common type of sleep apnea is Obstructive Sleep apnea syndrome (OSA). It is defined as sleep-disordered breathing distinguished by recurrent episodes of upper airway collapse during sleep [2].

It is caused due to the collapse of upper airway (pharynx) during sleep [4].In normal subjects, according to Bradley *et al.* [4], the onset of sleep does cause a partial withdrawal of the pharyngeal dilator muscle tone, but not sufficient to cause it to collapse. The main reason for this is due to the decrease in the lumen of the pharynx as a result of a layering of fat in obese patients [5]. Physiological observations of sleep apnea patients during apneic events have been recorded as follows [6]: during each episode of obstruction there is a decrease in oxygen saturation which is sometimes accompanied by a slowing heart rate; at the end of the episode the EEG is said to show a brief (3-10 seconds) burst of alpha activity; the electromyogram (EMG) is elevated and the heart rate is accelerated. After which breathing resumes and oxygen saturation returns to the level of wakefulness.

This pattern occurs recurrently throughout the night. This results in sleep fragmentation and hence the disorder is associated with daytime symptoms, most often

excessive sleepiness [1]. It is also known to play a key role in the pathogenesis of cardiac arrhythmias, arterial hypertension, heart failure etc [4]. It is also linked to cognitive decline, decreased memory etc [7].

1.3 Conventional Diagnosis of SDB

Currently OSA is diagnosed mainly by in-laboratory polysomnography (PSG). The electrophysiological measures used in clinical PSG's are left and the right electro-oculogram, electromyogram (submental muscle), electroencephalogram (C3/A2 or C4/A1 placements) to document sleep states; electrocardiogram to document cardiac arrhythmias; electromyogram (tibialis muscle) to identify periodic leg movements; nasal / oral airflow (thermistor), thoracic movement (strain guage), SaO2 (oxygen desaturation by oximetry) to document apnea and hypopnea events with associated desaturation [6]. At the end of the overnight sleep study a sleep specialist scores the polygraph recording, identifying sleep stages and events causing oxygen desaturation. From this analysis an Apnea Hypopnea Index (AHI) is calculated for the patient.

1.3.1 Apnea Hypopnea Index (AHI)

This index has been used to define the severity of OSA. It measures the frequency of reductions in airflow associated with upper-airway collapse or narrowing that occurs with the state change from wakefulness to sleep [2]. An apnea has been characterized as nearly complete cessation of airflow associated with oxygen desaturation or an arousal from sleep and involves upper airway collapse [2]. Studies define apnea as a breathing cessation of more than 10 seconds and hypopnea as being associated with a decrease of respiratory volume by 50% for more than 10 seconds [1].

The average number of apneas and hypopneas during one hour of sleep is called the apnea/hypopnea index (AHI) or respiratory disturbance index (RDI) [4]. A patient having an AHI between 5 and 15 is said to have mild OSA, whereas 15 to 30 is moderate and more than 30 events per hour is diagnosed as having severe sleep apnea [2,4]. These classifications also depend on factors such as sleepiness etc.

1.4 Electroencephalography (EEG) and Sleep

The onset of sleep is typically characterized by gradual changes in cortical electroencephalographic (EEG) activity. The EEG signal is of primary importance in interpreting polysomnography studies. It is the record of electrical potentials generated by the cortex and the deeper brain structures, namely the thalamus [6]. This measurement is due to the relative difference in potential between the two recording electrodes which maybe bipolar or unipolar. Bipolar records the potential difference between two cortical electrodes and unipolar records potential differences between a cortical electrode and a theoretically indifferent electrode on some part of the body distant from the cortex [8].

1.4.1 Sleep Rhythms

The surface EEG shows typical patterns of activity that can be correlated with various stages of sleep and wakefulness [6]. These patterns or rhythms are characterized by the frequency and amplitude of the electrical activity. The normal human EEG is observed to show activity over the range of 1-30 Hz with amplitudes in the range of 20-100 µV [6]. In an adult human whose resting with his eyes closed, the most prominent component of the EEG is the alpha rhythm whose frequency lies between 8-12 Hz and

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an amplitude of 50 μV [8]. Lower amplitude waves of frequency range 18-30 Hz have similarly been recorded during intense mental activity called Beta rhythm and frequency range 12-16 Hz as Sigma rhythm. Another pattern of large, regular waves of frequency range 4-7 Hz called theta rhythm have been recognized along with a slow wave of less than 4 Hz called the delta rhythm [8]. Theta and delta waves are normal during drowsiness and early slow-wave sleep and if observed during wakefulness, are a sign of brain dysfunction [6].

1.4.2 Sleep Stages

Sleep is said to be composed of a succession of sleep stages of two types: rapid eye movement (REM) sleep and non-REM (NREM) sleep [8]. NREM sleep is divided into four stages. A person falling asleep is observed to first enter stage 1 characterized by low-amplitude, high frequency EEG activity (loss of alpha rhythm). This is followed by stage 2 with the presence of sleep spindles of amplitude 50 μV and 10-14 Hz and K-complexes. Stage 3 consists of lower frequencies and increased amplitude followed by maximum slowing with large waves (Delta rhythm) as seen in Stage 4 [8]. REM sleep is observed as rapid, low voltage, irregular EEG activity associated with muscle atonia and rapid eye movements. Fragmented sleep, typical symptom of OSA, is believed to be caused mainly due to cortical arousals induced by apneic and hypopneic events [9].

1.5 Arousal in Sleep

Sleep in patients having sleep disorders and in some elderly patients is punctuated with frequent, brief arousals [10].The American Sleep Disorders Association (ASDA) have described the characteristics of an arousal in an attempt to

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standardize its identification. Arousals are observed to be transient and generally do not result in behavioral awakening, occurring as often as once per minute or more in some conditions. The arousing stimulus differs in various disorders and can be identified in some cases (i.e. apnea, leg movements, pain). These brief arousals are characterized by abrupt changes in electroencephalographic (EEG) frequency (which is suggestive of wake state) and/or brief increases in electromyographic (EMG) amplitude. They have defined an arousal as "*An abrupt shift in EEG frequency, which may include theta, alpha, and/or frequencies greater than 16 Hz but not spindles*" [10]. Spindles are defined as "*waxing and waning waves that have a frequency between 7-14 Hz, that are grouped in sequences that last 1 to 2 seconds and that occur periodically with a slow rhythm of 0.1 to 0.3 Hz*" [11].

1.5.1 Physiology of a Respiratory arousal

Studies have tried to explain the occurrence of a respiratory arousal namely arousals linked with progressive increases in stimuli related to respiration i.e. hypoxia (oxygen deficiency), hypercapnia (increase concentration of carbon dioxide) and respiratory effort. Berry et al. [12] have discussed various studies that observe the occurrence of respiratory arousals. Earlier studies focused on arousal thresholds as being values of PO_2 (or SaO_2) below which, or PCO_2, above which arousals occurred during sleep. Studies by Hedemark et al [13] determined that hypercapnia is a much more potent stimulus than hypoxia, as an increase in end tidal PCO_2 by 10-15 mmHg caused arousals to occur, whereas one study showed that human subjects failed to arouse from sleep during half the hypoxia trials even when arterial oxygen saturation

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fell as low as 70% [14]. This effect of oxygen and carbon dioxide levels on the brain was explained through a simple model which proposed that the chemoreceptors project directly to the areas of the brain responsible for arousal, such as the reticular activating system, such that when the stimulus transmitted from the chemoreceptors exceeds the arousal threshold, arousal occurs.

However, experiments were conducted to determine if upper airway narrowing or occlusion would be the primary cause of an arousal stimulus. A study performed on dogs by Yasuma et al. [15] compared the onset of arousal by isocapnic hypoxia (rebreathing) with and without an added expiratory load. They discovered that arousal occurred at a higher SaO_2 in the loaded condition which showed that both chemoreceptors and mechanoreceptors could result in an arousal stimulus during airway occlusion.

From analysis of previous studies Berry et al. [12] stated that the arousal stimuli related to respiration could be triggered by the following:

A. Chemical (chemoreceptors)

   Hypoxia,

   Hypercapnia and

   Net ventilatory drive

B. Mechanical (mechanoreceptors)

   Upper and lower airways,

   Respiratory muscles and

   Chest wall

A model to explain this relationship is shown by Berry *et al.* [12].
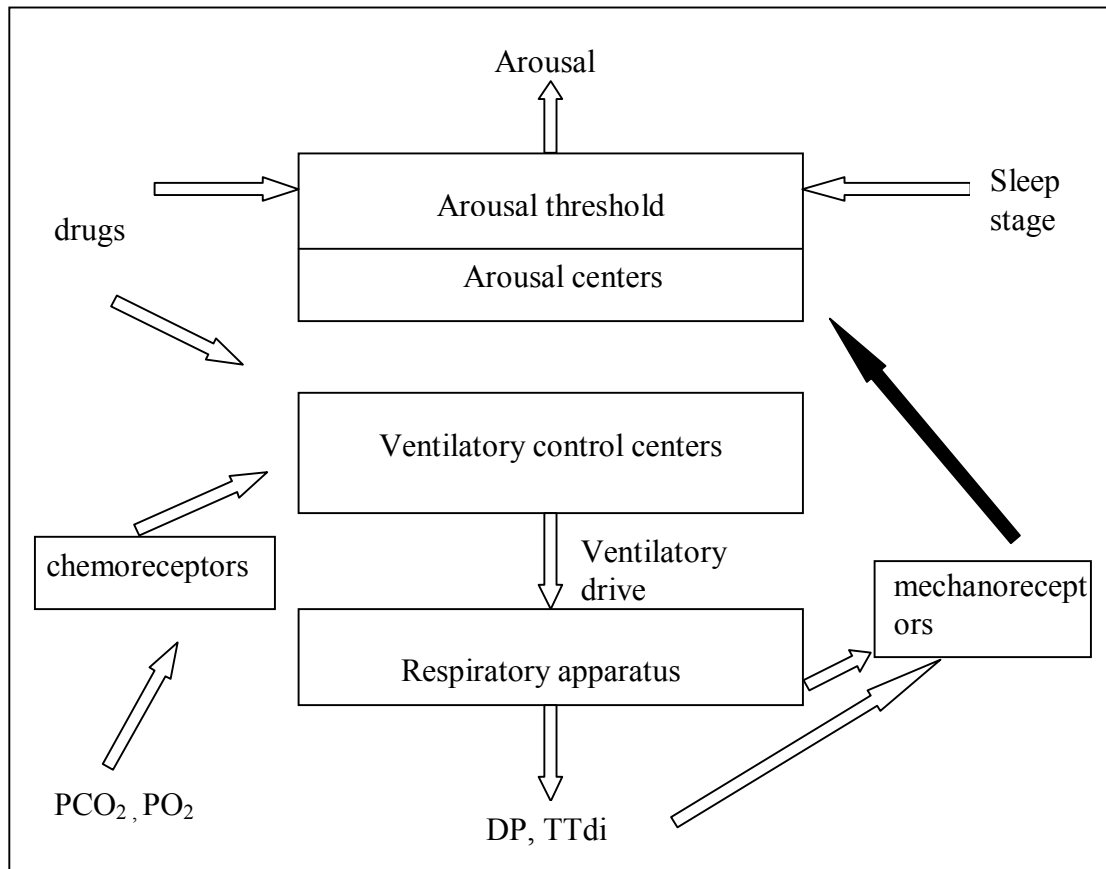
Fig. 1.1 Block Diagram of factors affecting Respiratory Arousal
(Adopted from Berry *et al.* [12])

The arousal stimulus is information got from the mechanoreceptors which are stimulated by the act of inspiration. The arousal stimulus is said to increase as the level of inspiratory effort increases. The esophageal pressure deflection (DP) or the tension time index of the diaphragm (TTdi) are assumed to be a reflection of the level of inspiratory effort and are hence considered as indices of the magnitude of the arousal stimulus. While changes in respiratory stimuli (PCO_2, PO_2 and mechanical factors) alter the time course of inspiratory effort (ventilatory drive) during airway occlusion,

arousal is said to occur once a given level of inspiratory effort is reached, independent of the combination of stimuli contributing to the ventilatory drive. Thus if mechanoreceptor output increased in proportion to inspiratory effort, then arousal would also be triggered at the same level of effort, independent of the combination of stimuli generating increased ventilatory drive. Thus the time to arousal (apnea duration) would depend on both the arousal threshold and the respiratory response to airway occlusion. Central nervous system depressants (ethanol, triazolam) or a deeper stage of sleep (stage 3/4) would raise the arousal threshold [12].

Some factors that influence the arousal threshold to airway occlusion have been known to be sleep stage, prior sleep fragmentation, central nervous depressants, and the possible factors are within-stage variations in depth of sleep, time of night (circadian, sleep cycles) and the amount of accumulated sleep [12].

<u>1.6 Literature Review</u>

According to literature, rapid electroencephalographic changes in response to cerebral anoxia were observed as early as 1925 [16]. Since then many researches have been conducted to record changes in EEG in patients with respiratory sleep disorders.

Dingli *et al*. [17] studied the presence of visible cortical arousals at the termination of apnoeas/hypopnoeas. They found that 77% of the events occurring in NREM 1 and 2 and 64% of the events in REM sleep were associated with arousal, when compared to a significantly lower number of 34% of events in NREM 3 and 4 (Slow wave sleep).

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In order to detect indices that would enable effective recognition of arousals, research was conducted by Drinnan *et al.* [18] which studied changes in amplitude and frequency during an arousal. Indices related to frequency were proved to be feasible in the automated detection of arousals. Further on Guilleminault *et al.* [16] reported a delta band amplitude increase starting on average 13 seconds after the onset of apnea. During NREM, the average differences between initial and maximal values were found to be 268% and 202% between initial and final values during the event duration. The variation in delta power was further studied by Berry *et al.* [19] who reported a cyclic increase in delta power which was in sync with increased respiratory effort in NREM sleep. This increase in delta power was also seen by Black *et al.* [20] who studied delta band activity surrounding increases in esophageal pressure in Upper Airway resistance syndrome patients. They observed an increase in delta band activity before the esophageal pressure reversal regardless of the actual presence of an arousal. There was also a recorded subsequent increase in alpha, sigma and beta activity that was significant. This change in EEG spectrum was studied by Dingli *et al.* [9] in events which were not associated with detectable arousals and compared to those events which were terminated by detectable cortical arousals. They performed spectral analysis surrounding the termination of events and found a significant decrease in theta band activity irrespective of arousal visibility in NREM sleep. During REM sleep though, they did not detect significant changes during events which did not have associated visible arousals. They also detected a significant increase in alpha and sigma bands in arousal terminating events in NREM sleep.

1.7 Overview of Analysis: Detection of SDB events using EEG

As literature study revealed changes in the EEG spectrum that occurred during the SDB events, the main focus of this study was to see whether these differences were identifiable using power spectral analysis and whether it could be applied to SDB detection. The study is divided into two parts. The first deals with the analysis of power spectral changes that occurs during the termination of an event. Previously scored apneic and hypopneic events were analyzed and changes that occurred in the sleep wave activity were observed. Threshold values corresponding to the changes in sleep waves that occurred at the termination of these events were chosen.

The second part of the study involved finding the changes in the power spectrum of the EEG data that crossed the chosen threshold values. This was implemented for the Control and the OSA subjects for the EEG signals collected for the entire night to determine if the detection of the SDB events is feasible.

1.8 Organization of Thesis

Following the introduction to the thesis in Chapter 1, the methods used to test the hypothesis that SDB events can be detected using EEG is explained in Chapter 2. This chapter also outlines the experimental setup used to extract the EEG data and the subject demographics. Chapter 3 goes on to show the results obtained after the implementation of the algorithm given in Chapter 2. The discussion of the results and limitations of the study are elaborated in Chapter 4 followed by the conclusion to the thesis in Chapter 5.

CHAPTER 2

METHOD

This chapter deals with the methods used to test the hypothesis that SDB events can be detected by changes in the power spectral density that occur due to the termination of these events by cortical arousals. It also gives the experimental setup and subject demographics that were taken into consideration while data was selected.

2.1 Characteristics of the EEG signal

Various methods that have been tried to extract quantitative features from an EEG signal have always faced challenges due to the fact that the dynamics of EEG depends on brain activities which in turn are related to processing of information that originates internally as well as externally. Previous investigators have revealed that the EEG signal was a highly non stationary process and it only could be described by the basic stochastic concepts for durations not longer than 10-20s [23]. A study showed that the variability of power of the main spectral EEG components for segments between 5 to10 s ranged up to 50-100% [24]. Hence they concluded that in order to determine its spectrum the signal should be analyzed as a series of stationary random processes [23]. Such processes have average values that are constant and autocorrelation functions that depend only on time differences. Stationary random processes do not have finite energy and hence do not possess a Fourier Transform. Such signals have finite average power and hence are characterized by a power density spectrum. In practice, a single

realization of the random process is considered and an estimate of the power spectrum of the process is computed [25].

<div align="center">2.2 Non parametric methods for Power Spectrum Estimation</div>

2.2.1 Using the periodogram

Representing a random signal by x[n] which exists for an infinite time duration, but having a finite segment of length L available for processing, where n is an integer ranging from n=0, 1... L-1. The truncated data can be shown as the product of the signal x[n] with a window function w[n]. Let S($e^{j\omega}$) be the Discrete Time Fourier Transform (DTFT) of $x[n] \cdot w[n]$

$$S(e^{j\omega}) = \sum_{n=0}^{L-1} x[n] \cdot w[n] e^{j\omega n} \tag{2.1}$$

where w[n] is nonzero for n=0, 1... L-1 and ω ranges between $\pm \pi$.

An estimate of the power spectral density is then given as

$$I_{xx}(e^{j\omega}) = \frac{1}{LU} |S(e^{j\omega})|^2 \tag{2.2}$$

Where U is a normalizing factor to remove any bias in the estimate that could be caused by the window w[n] and is defined as

$$U = \frac{1}{L} \sum_{n=0}^{L-1} |w[n]|^2 \tag{2.3}$$

$I_{xx}(e^{j\omega})$ is also called the periodogram if w[n] is a simple rectangular window function else it is known as the modified periodogram [22].

2.2.2 Using the Welch Method: Averaging Modified Periodograms

A method proposed by Welch [26] uses periodogram averaging in order to compute the estimated power spectra. This is illustrated as follows:

Let $X(j)$, $j=0,…,$N-1 be N samples from a stationary sequence. Let $X(j)$ have a spectral density $P(f)$, $|f|<1/2$. Consider segments of length L, possibly overlapping, such that the starting points of these segments are D units apart. Let $X_1(j)$, $j=0,…,$L-1 be the first such segment. Then

$$X_1(j) = X(j) \qquad\qquad j= 0,…,L\text{-}1. \qquad\qquad (2.4)$$

Similarly

$$X_2(j) = X(j + D) \qquad\qquad j= 0,…,L\text{-}1. \qquad\qquad (2.5)$$

Till

$$X_K(j) = X(j + (K\text{-}1)D) \qquad\qquad j= 0,…,L\text{-}1. \qquad\qquad (2.6)$$

This assumes that the entire record is covered i.e. (K-1) D+L=N.

For each of the segments having length L a modified periodogram is calculated. This is done by selecting a data window $W(j),j=0,…,$L-1 and forming sequences $X_1(j)$ $W(j),…$ $X_K(j)$ $W(j)$. Then, the finite Fourier transforms $A_1(n),…,$ $A_K(n)$ of these sequences are calculated, where

$$A_K(n) = \frac{1}{L}\sum_{j=0}^{L-1} X_k(j)W(j)e^{-2kijn/L} \qquad\qquad \text{where } i=(\text{-}1)^{1/2} \qquad (2.7)$$

Thus, the K modified periodograms are obtained,

$$I_k(f_n) = \frac{L}{U}\,|\,A_k(n)\,|^2 \qquad\qquad \text{for } k= 1,2,…,K, \qquad\qquad (2.8)$$

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where $f_n = \dfrac{n}{L}$ $n=0,\ldots, L/2$ (2.9)

and $U = \dfrac{1}{L}\displaystyle\sum_{j=0}^{L-1} W^2(j)$. (2.10)

The spectral estimate is the average of these periodograms, i.e.

$$\hat{P}(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n).$$ (2.11)
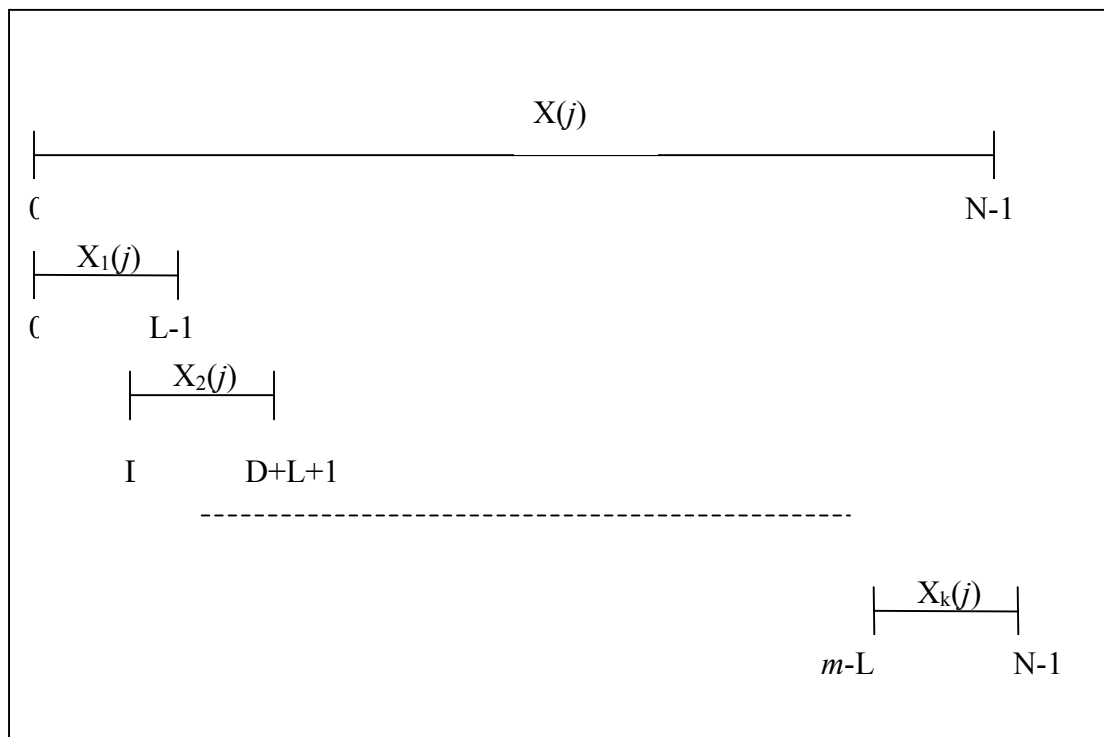
Fig. 2.1 Segmentation of data using Welch Method

The advantages of using the Welch method is the reductions in the number of computations its application in the case of non stationary sequences [26].

2.3 Experimental Setup

This study was based on data that was collected and processed by the SDB research group at UTA in collaboration with Sleep Consultants Inc., (Fort Worth, Texas). This data was accessed after obtaining the approval from the Office of Research Compliance at The University of Texas at Arlington.

2.3.1 Subject Demographics

Fourteen adult volunteer subjects, ages 46.21 ± 9.75 (SD) were chosen for this study. These were referred to as the control group (NOR) as they were recorded to have no cardiac or respiratory complications and also any sleep-related problems. Another group (OSA) of thirteen subjects, ages 49.08 ± 8.82 (SD), previously diagnosed with OSA was selected as well. The subject demographics of the NOR and OSA groups are shown in Table 2.1 and Table 2.2, respectively. The sleep expert scoring of their Apnea/Hypopnea Index (AHI) is also included.

Table 2.1: Subject Demographics for Control Subjects (n=14)

Subject ID	Gender	Age (Years)	Weight (kg)	Height (m)	BMI (kg/m^2)	AHI
S04	M	43	87	1.85	25.4	3
S05	M	36	66	1.73	22.1	6
S06	F	36	81	1.68	28.7	2
S07	F	58	64	1.60	25.0	0
S09	M	62	65	1.68	23.0	2
S11	M	49	95	1.75	31.0	4
S12	F	42	82	1.70	28.4	6
S13	F	40	61	1.60	23.8	2
S14	M	59	93	1.88	26.3	1
S15	F	35	46	1.58	18.4	0
S16	M	38	68	1.65	25.0	6

Table 2.1 Continued

S18	M	56	86	1.75	28.1	2
S19	F	54	57	1.60	22.3	3
S21	M	39	100	1.78	31.6	11
Mean ± SD		46.21 ± 9.75	75.07 ±16.20	1.70 ± 0.09	25.65 ±3.67	3.43 ±2.98

Table 2.2: Subject Demographics for OSA Subjects (n=13)

Subject ID	Gender	Age (Years)	Weight (kg)	Height (m)	BMI (kg/m^2)	AHI
S01	M	50	99	1.83	29.6	9
S03	M	38	91	1.88	25.7	4
S10	F	49	67	1.75	21.9	19
S20	M	39	157	1.90	43.5	70
S23	F	47	91	1.65	33.4	57
S24	M	37	64	1.63	24.1	8
S25	M	56	128	1.85	37.4	37
S26	F	44	89	1.70	30.8	20
S27	F	49	59	1.60	23.0	62
S28	M	49	100	1.80	30.9	14
S29	M	57	105	1.80	32.4	4
S30	F	54	92	1.52	39.8	30
S31	F	69	76	1.52	32.9	38
Mean ± SD		49.08 ± 8.82	93.69 ± 26.66	1.73 ± 0.13	31.18 ± 6.52	28.62 ± 22.72

2.3.2 The Experimental Setup

The experimental setup which was followed during data collection is explained in this section.

Each subject was tested for one night for approximately 8 hours. The standard polysomnographic (NPSG) data, which included electrocardiogram (EKG), EEG, EOG

and chin electromyogram (EMG), were recorded on the data acquisition computer (Telefactor, Conshocken, Pennsylvania) after being preprocessed by the Nihon Kohden polygraph (Irvine, California). The gain and sensitivity settings on the polygraph were adjusted for each subject to accommodate for saturation of signals. The respiratory activity of the subject was measured using a pneumotachtometer (Hans Rudolph Inc., Kansas City, Missouri) which was connected to a pressure transducer (Validyne MP45-871, Northridge, California). The signal from the transducer was sent to a signal conditioning unit (Validyne MC1-333) which was recorded by the computer. Piezo electric abdominal and chest bands were attached to the subject to record the abdominal and chest movements. Blood oxygen saturation (SpO_2) was measured using a pulse oximeter, with a finger probe. A total of eighteen (18) channels were recorded. The NPSG data was collected on a Telefactor whose maximum sampling rate is 100 Hz.

As the ECG signals were to be sampled at rates greater than 250 Hz the signals from the nine ECG leads were collected on the Dell Notebook Inspiron 4100, Intel Celeron@ 1.06GHz; 256MB RAM (Round Rock, Texas) using the NI DAQ 6024E PCMCIA card (National Instrument, Austin, TX).

Following the 10-20 System of electrode configuration, the electrode placement for the EEG signal was C3 and A2. Two additional EEG signals recorded from the forehead were intended for a separate study. This study concentrated on the EEG data that was obtained from the electrode placement at C3 and A2 (Appendix A)

A synchronization (SYNC) signal was generated in the laptop computer that was fed into the telegraphic computer. This provided a means to synchronize the data collected on the two computers with independent clocks. (31, 32)
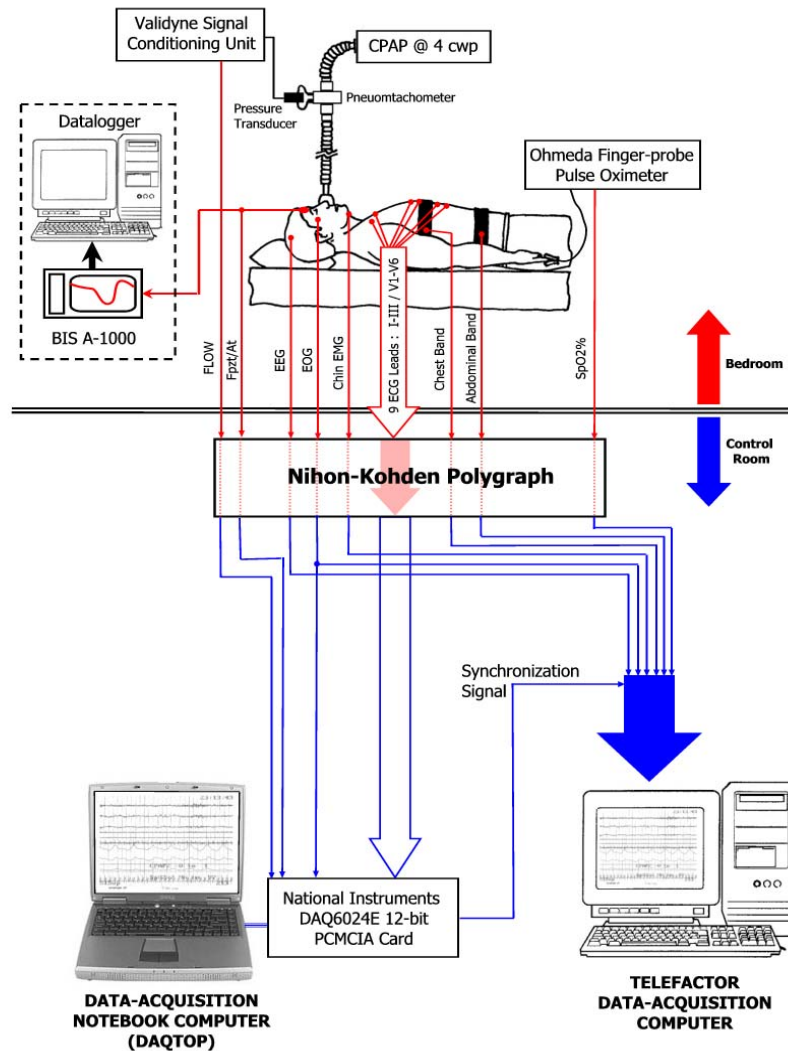
Fig. 2.2 Schematic of the data collection setup
[Adopted from Sridhar Vijendra [32]]

2.4 Data Visualization

In order to view the data obtained from the telefactor a graphical user interface called *DataBrowser* was developed in Matlab by Sridhar Vijendra [32]. This enables the user to view up to 4 channels of data having different sampling rates, with corresponding sleep stage and apnea event annotation. The data collected from a subject during the entire night can be viewed and saved for later or epochs as along as 15 minutes can be stored at a time. The sleep stages and apnea events are scored and identified as different numbers that can be viewed along with the EEG signal in the *DataBrowser* window. This information is given in Table 2.3.

Table 2.3 Numeric Representation for Sleep Stages and Apnea Event Annotation

Numeric Representation of sleep stages		Numeric Representation of apnea events	
Subject Awake	0/9	Obstructive Event	1
Sleep Stage 1	1	Mixed Event	2
Sleep Stage 2	2	Central Event	3
Sleep Stage 3	3	Hypopnea	4
Sleep Stage 4	4	No event (Normal Breathing)	10
REM sleep	5	Unclassified	0
Movement	6		
Unclassified	10		
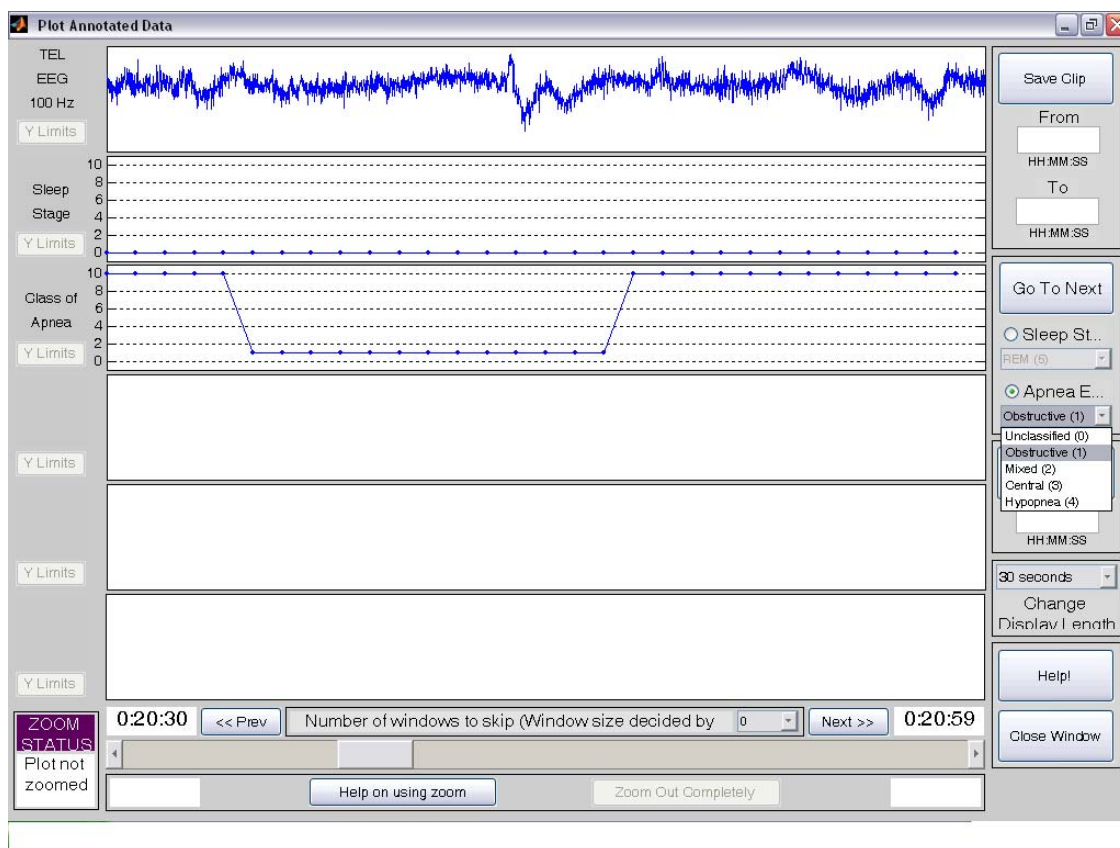
Fig. 2.3 DataBrowser window showing Sleep staging and apnea staging

2.5 Analysis of EEG Signal

The following section deals with the preparation of the data in order to analyze the power spectrum of the EEG signal and the algorithm used in order to estimate the power spectral density of the data.

2.5.1 Clip Preparation for Study of Single Events

Apneic and hypopneic events were clipped from the EEG signal that contained the entire night study of each individual subject using the program *ReadClipApnea* (32) and the program *ClipFile* (Appendix C) written in Matlab®. Each clip contained 10 s of data before the start of the event, the entire duration of the event, and 10 s after the event termination.

The apnea and hypopnea events were scored previously by a certified sleep specialist who was blind to the objective of this investigation. In order to identify power spectral changes around the apneic/hypopneic event terminations, EEG data corresponding to these specific terminations were studied. These terminations were identified by the apnea scoring information obtained from the DataBrowser. When the apnea event annotation changed from 1 (Obstructive event) or 4 (Hypopnea event) to 10 (Normal Breathing), this point was established as the termination of the respiratory event. Spectral analysis was performed on the EEG data for a 10 s window before the event termination and in a 10 s window after the event termination.

This window size was recommended by Dingli et al. [9] in order to maintain stationarity required for FFT analysis as explained in Section 2.1 and was retained after suitable results were obtained during the first part of the study.
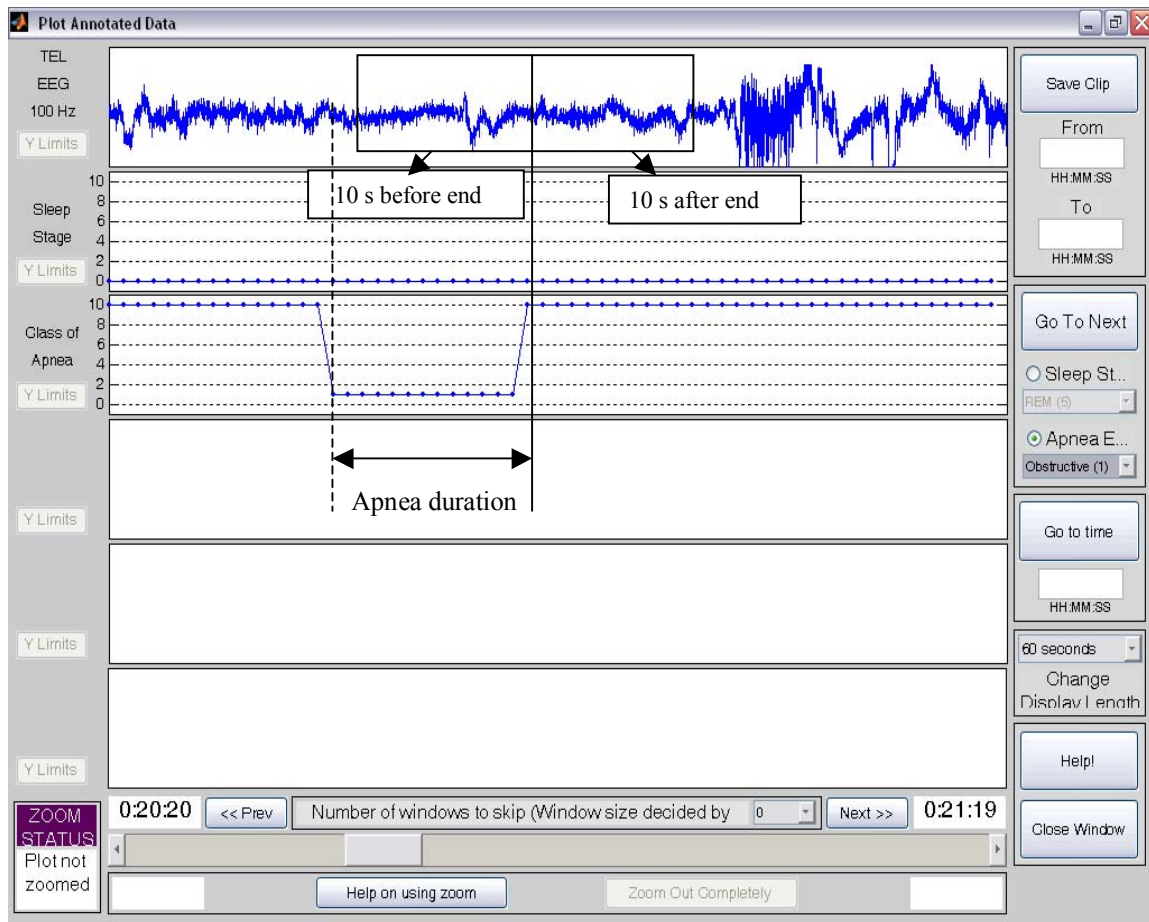
Fig 2.4 Window duration used in investigation of power spectral changes around apnea termination.

2.5.1.1 Removal of DC offset

In a majority of the EEG examinations, scalp electrodes that are used are not in direct contact with the tissue. An indirect contact is established by the electrolyte bridge that is formed by an electrode jelly that is applied between the electrode and the skin. A steady potential (DC offset voltage) is created at this junction depending on the electrolyte composition and the condition of the skin which can be as large as the

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magnitude of the electrical activity recorded from the brain [27]. The DC component was removed from the clipped signal by removing the best straight line fit from the data. This is necessary before performing FFT on the signal. This was performed by MATLAB$^{®}$ function *detrend*

Given below is an example of a data clip that demonstrates the removal of DC offset.

(a)

(b)
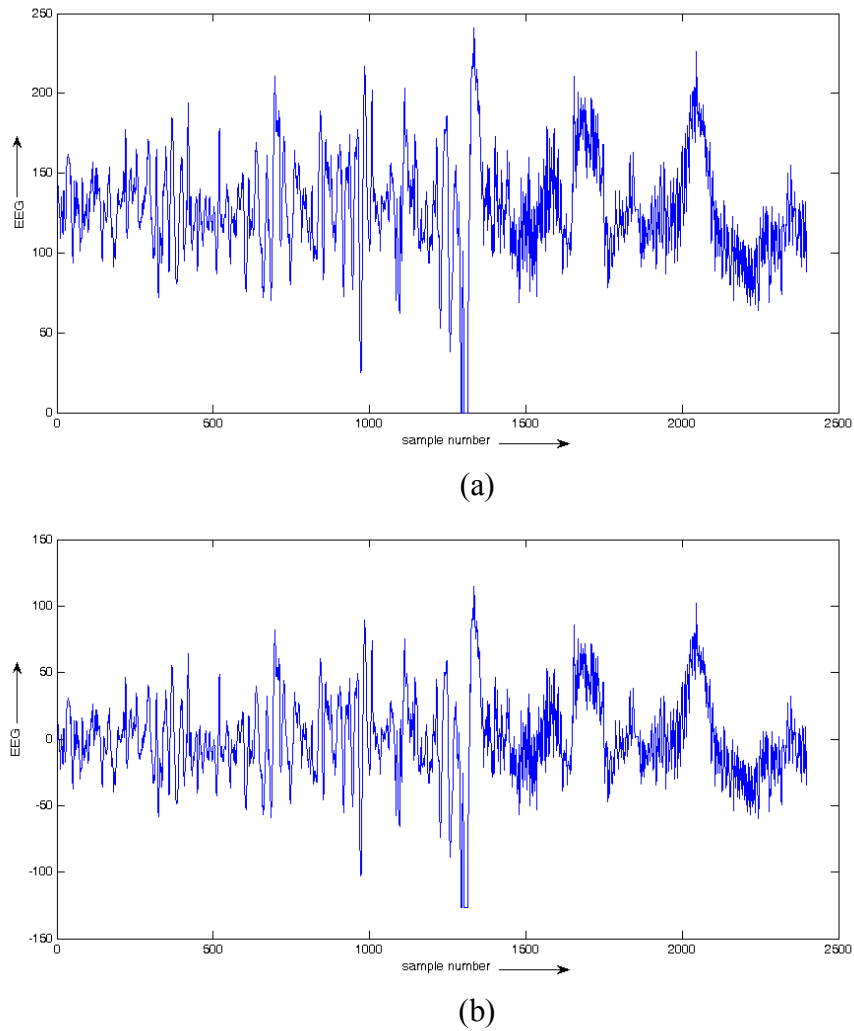
Fig 2.5 EEG clip data having DC offset (a) and having DC offset removed (b)

2.5.1.2 Removal of high frequency components using a low pass FIR filter

The DC offset free EEG signal was then filtered using an FIR (Finite Impulse Response Filter) low pass filter with a cut off frequency at 25 Hz. An FIR filter of order 200 was designed using a Hanning window (Appendix B). This was performed by MATLAB$^®$ function *fir1*. The output of the filter was then reversed and passed through the filter again in order to remove phase distortion produced by the filter. This was implemented using the MATLAB$^®$ function *filtfilt*.

2.5.2 Calculation of the Power spectral density (PSD)

The clipped data was prepared for analysis as described in Section 2.5.1. The EEG data in the 10s window before and 10s window after the event terminations were analyzed. The power spectral density estimate was calculated using the Welch Method of averaged periodograms, as explained in Section 2.2.1, using a 128 bin Hamming window with 64 points overlap (50% overlap). The resolution of the transformation into the frequency domain was chosen to be 0.015 Hz [9]. This was performed by creating a Welch object in MATLAB$^®$ by using the function *spectrum.welch* and applying it in the function *psd* written in MATLAB$^®$. This results in an average power spectral density curve (μV^2 /Hz) that lies over the frequencies $\pm \pi$.

2.5.2.1 Calculation of N point FFT for Power Spectrum Estimation

Suppose that the signal representation in the frequency domain is X(ω) and is periodic with a period 2π, only samples in the fundamental frequency range are necessary to compute. Considering the frequency domain is sampled at N equidistant

samples, and then the interval between two successive samples is $\delta\omega$ [25, p 436]. This is written mathematically as:

$$\delta\omega = \frac{2\pi(f=1)}{N} \qquad (2.12)$$

Assuming $\delta\omega = 0.015 * 2\pi$ radians

Here the discrete time frequency $f= 1$ Hz which corresponds to an analog frequency of 100 Hz. This relationship is shown in [25, p 22] as

$$f = F/F_s \qquad (2.13)$$

where F= analog frequency and

F_s =the sampling frequency (100 Hz)

Thus

$$N = \frac{2\pi * 100}{2\pi * 0.015}$$

$$= 6666.66$$

We consider N=8192 (next power of 2) and $\delta\omega$ =0.012 Hz

The estimated power spectrum using Welch method is thus obtained from Eq. (2.11)

$$\hat{P}(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n)$$

At frequencies $f_n = n/N$ [25] where $n= 0,1,...,N-1$ $\qquad$ (2.14)

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2.5.2.2 Calculation of area under the power spectral density estimate curve corresponding to the sleep rhythms

The average power of the sleep waves namely, delta (1-4 Hz), theta (4-8 Hz), sigma (8-12 Hz) and alpha (12-16 Hz) were calculated by finding the area under the spectral curve corresponding to the frequency bands.

To calculate points in the PSD curve corresponding to Delta band (1-4 Hz) Eq. (2.12):

n corresponding to 1 Hz = $1/\delta\omega$ = 1/ 0.012 = 81.92 ~ 82

n corresponding to 4 Hz = $4/\delta\omega$ = 4/ 0.012 = 327.68 ~328

Therefore average delta power (μV^2) is the area under the PSD curve corresponding to points 82-328.

Similarly to calculate Theta band (4-8 Hz)

n corresponding to 4 Hz = $4/\delta\omega$ = 4/ 0.012 = 327.68 ~ 328

n corresponding to 8 Hz = $8/\delta\omega$ = 8/ 0.012 = 655.36 ~ 656

Therefore average theta power (μV^2) is the area under the PSD curve corresponding to points 328~656.

Similarly to calculate Alpha band (8-12 Hz)

n corresponding to 8 Hz = $8/\delta\omega$ = 8/ 0.012 = 655.36 ~ 656

n corresponding to 12 Hz = $12/\delta\omega$ = 12/ 0.012 = 983.04 ~ 984

Therefore average alpha power (μV^2) is the area under the PSD curve corresponding to points 656- 984.

Similarly to calculate Sigma band (12-16 Hz)

n corresponding to 12 Hz = $12/\delta\omega$ = 12/ 0.012 = 983.04 ~ 984

n corresponding to 16 Hz = $16/\delta\omega$ = 16/ 0.012 = 1310.72 ~ 1311

Therefore, average sigma power (μV^2) is the area under the PSD curve corresponding to points 984-1311.

The area was determined by using the Trapezoidal Integration method which works on the principle of splitting the area under a curve into trapezoids such that their summation gives the approximate value of the integral. This was performed by MATLAB® function *trapz*.

The values of power obtained for each frequency band was normalized by the average power of the signal, in the frequency range considered, to obtain power ratios. For e.g,

$$\text{Normalized power of Delta band} = \frac{\text{Area under PSD curve between points 82 to 328}}{\text{Area under PSD curve between points 82 to 1311}}$$

For the first part of the study analysis of the clipped files were performed using the program *PSDAnalysisClipFile* written in MATLAB® as given in Appendix C.
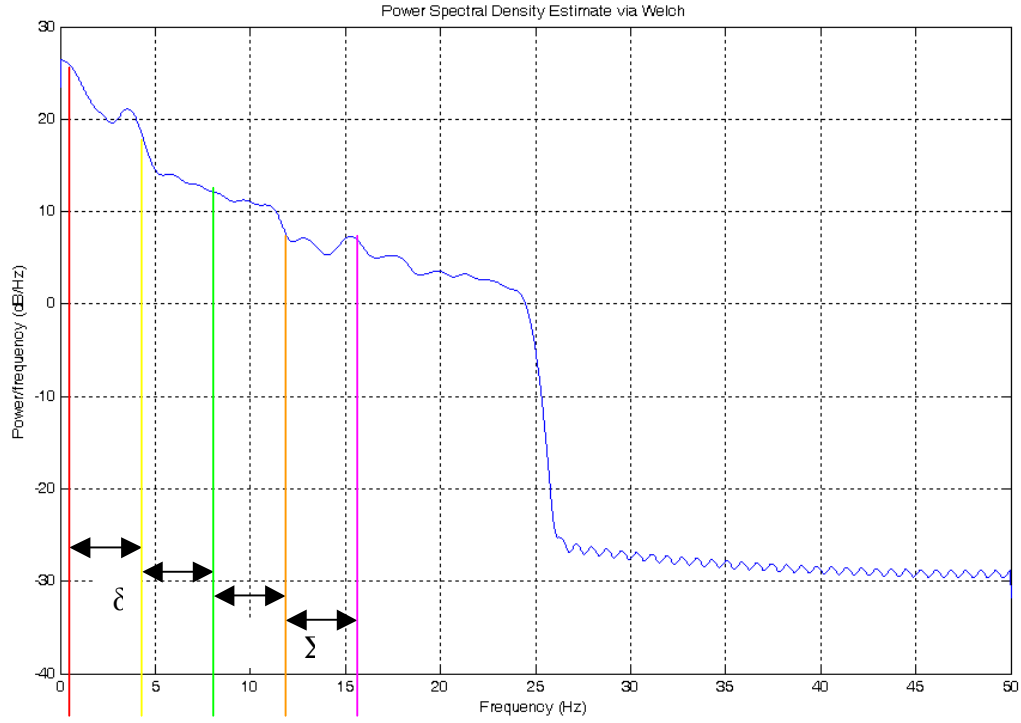
Fig. 2.6 Power spectral density estimate curve of a 10s signal epoch, showing the area under the curve corresponding to average power of delta, theta, alpha and sigma bands.

2.5.3 Identifying power spectral changes in EEG data of entire night duration

From the preliminary study, power ratios for the respective sleep waves were calculated for 10s duration before the event termination and 10s after the event termination [Section 2.5.1]. The differences in the power ratios before and after event termination were calculated for all the events during the entire night for the subjects. From this observation four threshold values for respective frequency bands of Delta, Theta, Alpha and Sigma were chosen, corresponding to differences in normalized power between the two 10s windows. This implied that differences in power ratios

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across two adjacent 10s windows crossing these threshold values signified event occurrence.

Two adjacent 10s sliding windows were applied to the start of the EEG data that contained information of a single subject for the entire night. PSD estimate using Welch method was calculated for both windows separately from which average power corresponding to respective frequency bands of Delta, Theta, Alpha and Sigma were calculated by finding the area under the PSD estimate curve corresponding to these bands. These values were normalized by the average power of the signal in the 10 s window within the frequency range considered. The difference between corresponding power ratios were computed between the adjacent windows and compared to the given threshold values.

If the differences crossed the threshold values and if an event had not been scored in the past 10 s, then an event is recorded as having occurred. The minimum 10 s EEG between scoring of arousals is taken into consideration as stated by the ASDA [10]. The 10 s sliding windows are moved further down the signal by five seconds and the process is repeated.

2.5.3.1 Algorithm

Step 1.EEG signal is extracted.

Step 2.DC component is removed.

Step 3.Signal is passed through a low-pass FIR filter of cut off frequency of 25 Hz.

Step 4.Two adjacent 10 s windows are placed at the start of the signal.

Step 5.Average PSD is estimated using Welch Method for the 2 windows separately.

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

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

Step 8. Difference in power ratios of corresponding frequency bands are calculated between the two 10 s windows.

Step 9. If Delta power ratio > Delta threshold and either

Alpha power ratio < Alpha threshold OR

Theta power ratio < Theta threshold OR

Sigma power ratio < Sigma threshold

And if no event has been scored in the past 10 s

Then an event termination has occurred.

Step 10. Slide the window by 5 s and Repeat Step 5 to 9 for the entire signal duration.

The implementation of the algorithm is written in the program *Detection_Events_Entire_Night.m* written in MATLAB® as given in Appendix C.

2.5.4 Calculation of Power Spectral Density Estimate for the EEG signal of entire night duration

In order to calculate the average power for individual frequency bands for the entire night, a 10 s window was applied to the start of the signal, after the initial steps of DC component removal and low pass filtering were performed. The PSD estimate was calculated for the 10 s window and the average power of frequency bands delta, theta, alpha and sigma were calculated and then normalized. The window was then moved by

10 s and the similar process of PSD estimation and average power of the frequency bands were followed.

Once the sliding window had moved through the entire signal, the normalized power of each frequency band from every 10 s window was considered and the mean was found for respective bands of delta, theta, alpha and sigma.

2.5.4.1 Algorithm

Step 1.EEG signal is extracted.

Step 2.DC component is removed.

Step 3.Signal is passed through a low-pass FIR filter of cut off frequency of 25 Hz.

Step 4.A 10 s window is placed at the start of the signal.

Step 5.Average PSD is estimated using Welch Method for the 10 s window.

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

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

Step 8.The 10 s window is moved by 10 s and the Steps 5 to 7 are performed till the window reaches the end of the signal.

Step 9.The normalized powers corresponding to each frequency band as obtained from Step 7 are considered and the mean of each band is found.

The implementation of the algorithm is written in the program *PSD_EntireNight* written in MATLAB$^{®}$ as given in Appendix C.

CHAPTER 3

RESULTS

This chapter deals with the results obtained in the first part of the study showing power spectral density changes around SDB event terminations and the further analysis of detection of SDB events from EEG data obtained during the entire night.

3.1 Preliminary Results - Analysis of Apnea/Hypopnea Event terminations

As discussed in Section 2.5 the normalized power of the frequency bands (delta, theta, alpha and sigma) were calculated 10 sec before the event termination and 10 sec after the event termination. A total of 201 apneas and 2016 hypopneic events were considered for analyses which were clipped from the OSA group. The duration of apnea and hypopnea events analyzed are given in Table 3.1 Table 3.2 gives the mean normalized power values for each OSA subject before and after event terminations.

Table 3.1 Number and duration of apnea/hypopnea events studied

OSA	Number of A/H	Mean duration (s) ± SEM (s)
Subj#1	38	23.50 ± 3.81
Subj#3	26	32.42 ± 6.36
Subj#10	112	29.38 ± 0.83
Subj#20	454	21.41 ± 0.39
Subj#23	293	31.05 ± 1.81
Subj#24	33	32.27 ± 5.62
Subj#25	236	28.78 ± 1.87
Subj#26	400	30.56 ± 1.53
Subj#27	115	27.90 ± 2.60
Subj#28	88	33.65 ± 3.59
Subj#29	25	38.96 ± 7.79
Subj#30	212	28.83 ± 1.98
Subj#31	183	27.09 ± 2.00
Mean ± SD		29.68 ± 4.44

Table 3.2 Normalized power of frequency bands around AH event terminations in OSA

OSA	10s BEFORE EVENT TERMINATION				10s AFTER EVENT TERMINATION				Intra-subject t-Test comparison for pre and post event terminations (p value)			
	Delta	Theta	Alpha	Sigma	Delta	Theta	Alpha	Sigma	Delta	Theta	Alpha	Sigma
Subj#1	0.5698	0.1794	0.1354	0.1137	0.5303	0.1735	0.174	0.1204	0.1208	0.3355	0.0211	0.3049
Subj#3	0.5202	0.353	0.0819	0.0427	0.4425	0.4061	0.0988	0.0504	0.0163	0.0411	0.0220	0.1406
Subj#10	0.6842	0.1918	0.0687	0.0538	0.6092	0.1981	0.097	0.094	4.3E-06	0.2355	4.5E-07	4.1E-07
Subj#20	0.6166	0.214	0.1049	0.0626	0.5352	0.2311	0.1329	0.0989	1.3E-24	1.8E-05	3.5E-22	1.1E-27
Subj#23	0.5799	0.2776	0.1001	0.0406	0.5355	0.2994	0.1148	0.0485	4.9E-06	0.0017	1.1E-06	1.2E-05
Subj#24	0.638	0.1958	0.0978	0.0668	0.558	0.2506	0.1124	0.077	0.0028	0.0004	0.0732	0.1763
Subj#25	0.4687	0.2744	0.1849	0.0701	0.4352	0.2896	0.1967	0.0765	0.0010	0.0151	0.0145	0.0146
Subj#26	0.7165	0.1901	0.065	0.0269	0.6264	0.2521	0.0822	0.0375	1.9E-23	6.2E-20	2.2E-10	3.5E-10
Subj#27	0.6528	0.1897	0.1188	0.037	0.5914	0.226	0.1337	0.047	2.9E-05	9.5E-05	0.0356	0.0017
Subj#28	0.5357	0.1857	0.1728	0.104	0.4625	0.1897	0.2281	0.1177	0.0003	0.2970	0.0002	0.0478
Subj#29	0.6993	0.1474	0.0793	0.0726	0.5639	0.1776	0.1176	0.1393	1.1E-05	0.0322	0.0007	0.0001
Subj#30	0.6512	0.1794	0.1125	0.0552	0.5394	0.2245	0.1553	0.0789	9.4E-19	3.4E-12	3.5E-14	2.9E-12
Subj#31	0.5277	0.2292	0.1711	0.07	0.3736	0.2643	0.2616	0.0982	7.2E-24	5.2E-06	7.5E-17	5.2E-11
Mean± SEM	0.604± 0.0214	0.215± 0.0154	0.114± 0.0112	0.062± 0.0069	0.523± 0.0206	0.244± 0.0174	0.146± 0.0151	0.083± 0.0088				
t-Test comparison for pre and post terminations (p value)	1 E-06	0.0002	0.0001	0.0007								

Mean Normalized Power Before and After SDB Event Termination
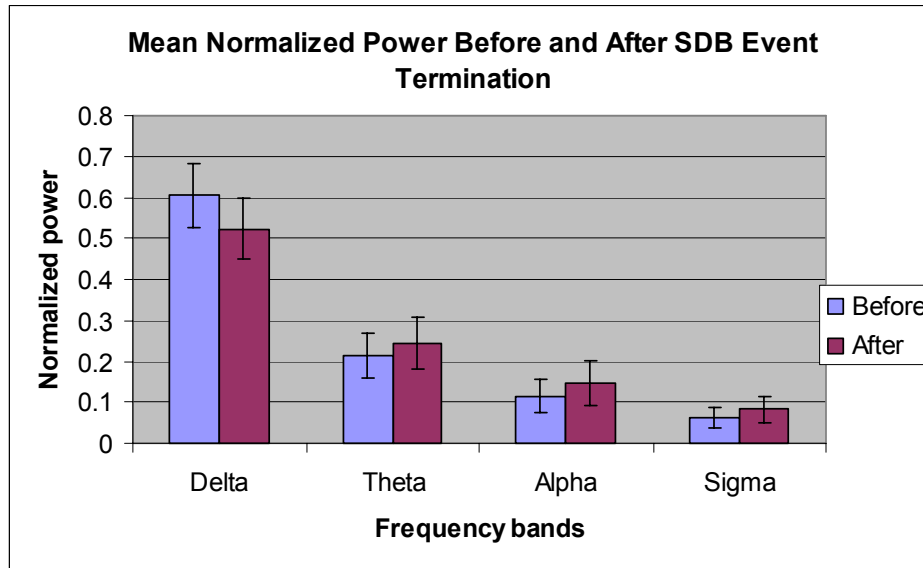
Fig 3.1 Comparison of mean normalized power around SDB event terminations

The mean values of the frequency bands for each subject from OSA group are compared before and after event terminations as shown in table 3.2. For e.g. Subj#1, 38 events are analyzed and the mean values of the frequency bands before and after event termination are shown. The intra subject comparison for these frequency bands before and after event terminations are also given. The mean and SEM (Standard Error of Mean) values of the frequency bands delta, theta, alpha and sigma, corresponding to the event terminations, for the entire OSA group, are depicted in Fig 3.1. A paired T-Test was performed, with a p-value <0.05 considered significant. Delta band (1-4 Hz) decreased significantly (p=1.34E-06); Theta band (4-8 Hz) showed a significant increase (p=0.0002), Alpha band (8-12 Hz) also showed a significant increase (p=0.0001) along with a significant increase in Sigma band (12-16 Hz) (p=0.0007). These differences are also significant in the intra subject comparison using t-Test. This difference was hypothesized to be due to the occurrence of a cortical arousal as

explained in Section 1.5. In order to identify cortical arousals linked with increased respiratory effort (SDB events), an increase in delta frequency during SDB events followed by its decrease at the termination of the event, was chosen as the first marker [15, 18, 19]. This decrease in delta frequency along with an increase in alpha, theta or sigma (higher frequencies) after the event termination, was chosen to indicate the presence of an SDB event.

3.2 Detection of SDB during the entire night in OSA and Control Subjects

From the preliminary analysis the threshold values for differences in normalized power for the frequency bands were chosen. The threshold was chosen by observing the normalized power value differences across the event terminations. Data clips not associated with apnea/hypopnea were selected and analyzed in a similar manner. The lowest possible normalized power difference corresponding to delta, theta, alpha and sigma were chosen as thresholds, values above which signified event termination.

Delta difference was set at 0.15, Theta at -0.1, Alpha at -0.045 and Sigma at -0.05. This was applied to the control group (n=14) and the OSA group (n=13) by using the algorithm explained in Section 2.5.3 Table 3.3 and Table 3.4 list these observations.

Table 3.3 SDB detection from the entire night data in Control Group (n=14)

Control	Manual Scoring parameters				Number of normalized power differences crossing the set threshold	Distribution of epochs crossing the set threshold				
	AHI	Irregular respiratory events	Sleep Stage Shifts	Number of Events scored manually (Apnea/Hypopnea)		Detection during occurrence of apnea	Detection during occurrence of Hypopnea	Detection during Stage changes from Deeper to Lighter sleep	Detection during Stage changes from Lighter to Deeper sleep	Detection during no stage transition
Mean ± SD	3 ± 3	19 ± 19	183 ± 79	14 ± 16	400 ± 157	1 ± 2	13 ± 15	37 ± 24	27 ± 16	325 ± 126

Table 3.4 SDB detection from the entire night data in OSA Group (n=13)

OSA	Manual Scoring parameters				Number of normalized power differences crossing the set threshold	Distribution of epochs crossing the set threshold				
	AHI	Irregular respiratory events	Sleep Stage Shifts	Number of Events scored manually (Apnea/Hypopnea)		Detection during occurrence of apnea	Detection during occurrence of Hypopnea	Detection during Stage changes from Deeper to Lighter sleep	Detection during Stage changes from Lighter to Deeper sleep	Detection during no stage transition
Mean ± SD	29 ± 23	181 ± 149	235 ± 41	170 ± 143	475 ± 104	14 ± 29	147 ± 104	32 ± 20	21 ± 14	259 ± 124

Table 3.4 shows the mean number of apneas (14 ± 29) and hypopneas (147 ± 104) detected from the EEG signal obtained from the entire night for the OSA group. The comparison between the mean number of events scored manually by a sleep specialist (170 ± 143) and the mean number of events detected automatically (475 ± 104) by the developed algorithm are shown. In addition to the events detected automatically that coincided with the manual scoring (32 ± 20, 21 ± 14), there were other epochs relating to sleep stage change and also during no sleep stage change that crossed the set threshold values (259 ± 124).

Table 3.3 shows the detection of SDB events in the control group. Similar comparison between the SDB events scored manually and those detected automatically are shown as that of the OSA group.

The data obtained for individual subjects is given in Table 1 and 2 [Appendix D]

3.2.1 Relation between manual scoring and automatic scoring of SDB events

Since there were a number of events detected that coincided with sleep stage changes along with those coinciding with the manually scored SDB events, a correlation between the sum of the irregular respiratory events and sleep stage changes that were scored manually and that of the SDB events detected by the Algorithm was performed.

Fig 3.2 (a) shows this correlation for control group and Fig 3.2 (b) shows this correlation for the OSA group. Data for each is given in Table 3 and 4 [Appendix D].
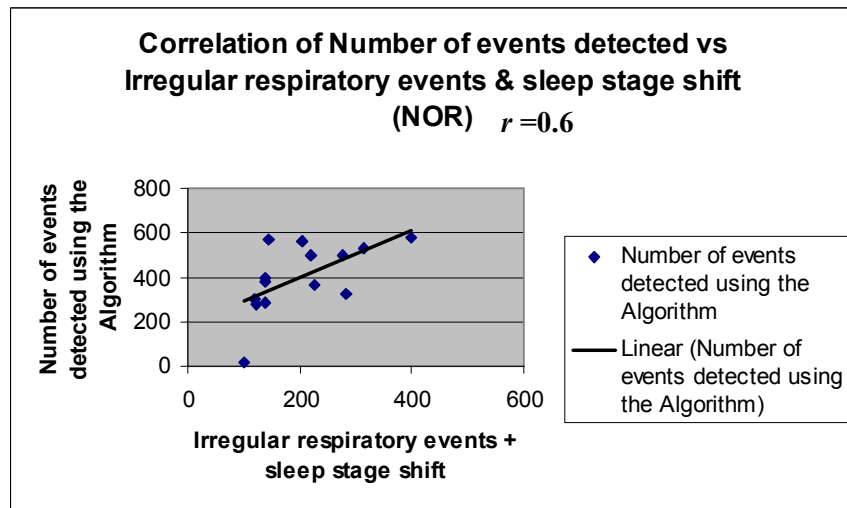
(a)
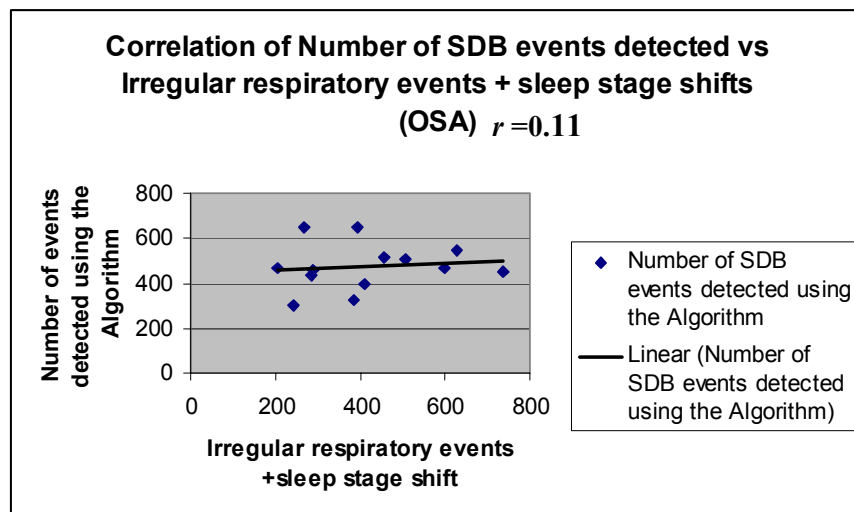
(b)

Fig. 3.2 Correlation between Number of SDB events detected and the sum of irregular respiratory events and sleep stage shifts in Control (a) and OSA (b)

The comparison was performed using Pearson's product moment correlation and the value was found to be positive in both OSA and Controls, showing that the two variables increase in value together. This relation is more correlated in the case of Controls (r=0.6).

The SDB events detected are verified for their time of occurrence with respect to apnea annotation. Fig 3.3 depicts the Pearson's product moment correlation between the number of AH events that were detected by the algorithm and those that coincided with manual scoring of AH events for OSA subjects (r= 0.98) and for Control (r=0.94) [Table 5 and Table 6, Appendix D].
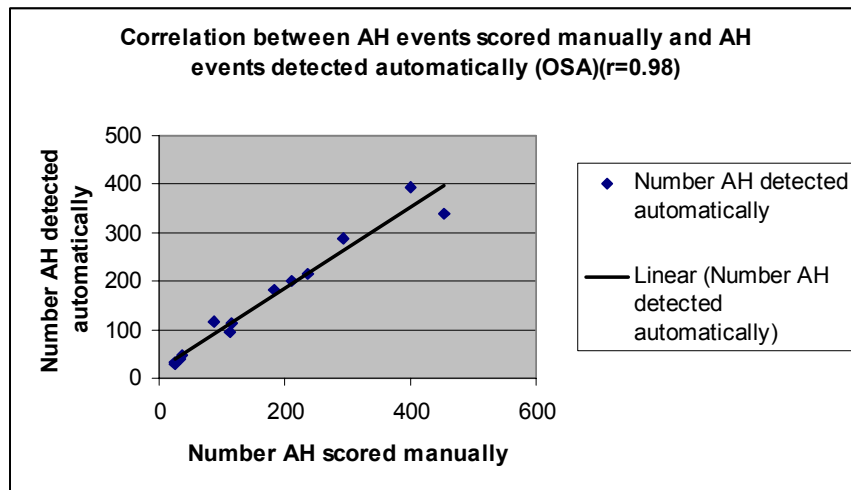
Fig 3.3 Correlation between AH events scored manually and
AH events detected automatically

The events that were detected that did not correspond to previous manually scored AH events (non apneic/hypopneic event detections) were studied with respect to their occurrence during sleep stage changes or no transition in sleep stage.

Fig 3.4 gives a percentage distribution of the apneic and non apneic event detections, with respect to the total number of events detected in each OSA subject, considering manually scored apnea annotation and sleep scoring.

Percentage distribution of Event detection during the entire night

Legend:
- % of events detected during AH events
- %of events detected during shift to lighter sleep stage
- %of events detected during shift to deeper sleep stage
- %of events detected during no sleep stage shift

(X-axis: OSA subjects — S1, S3, S10, S20, S23, S24, S25, S26, S27, S28, S29, S30, S31; Y-axis: Percentage Detection, 0–100)

Fig 3.4 Percentage distribution of Event detection during the entire night

3.2.2 Comparison of Mean normalized power differences between true and false Detections

In order to determine whether the difference in mean normalized power values, for the epochs coinciding with manually scored SDB events (true detection), were significantly different from those that did not (false detection) , the two-sample unequal variance T-Test was performed. This is depicted in figure 3.5 for the OSA group [Table 5, Appendix D].

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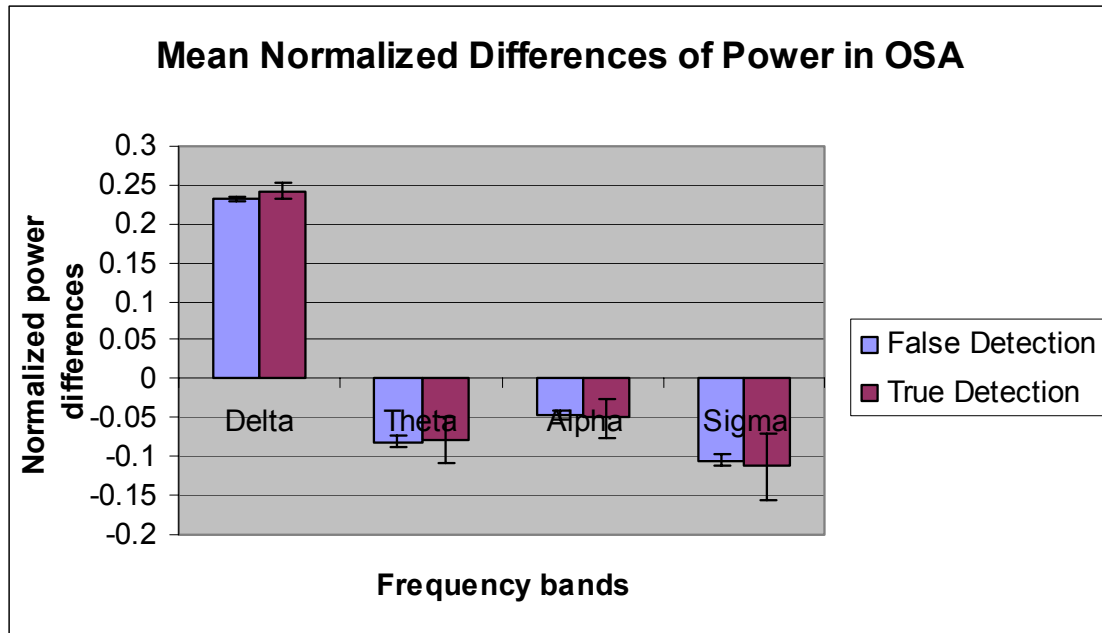
Fig 3.5 Comparison of mean normalized differences of power between false and true detections

The above results show that the normalized power differences of delta, theta, alpha and sigma do not show significant differences between those epochs that crossed the thresholds coinciding with Apena/Hypopnea events and those that did not correspond to such events. Further analysis is performed later to compare normalized power differences between epochs coinciding with sleep stage transitions and those coinciding with Apnea/hypopnea events.

3.3 Average power of Sleep wave bands for the OSA and Control Groups

The normalized power values for the frequency bands delta, theta, alpha and sigma were calculated for the entire night using a 10 second sliding window and were averaged for each subject in the OSA and Control group (Refer Section 2.5.4). This comparison is shown in Table 6 [Appendix D] and Fig. 3.6
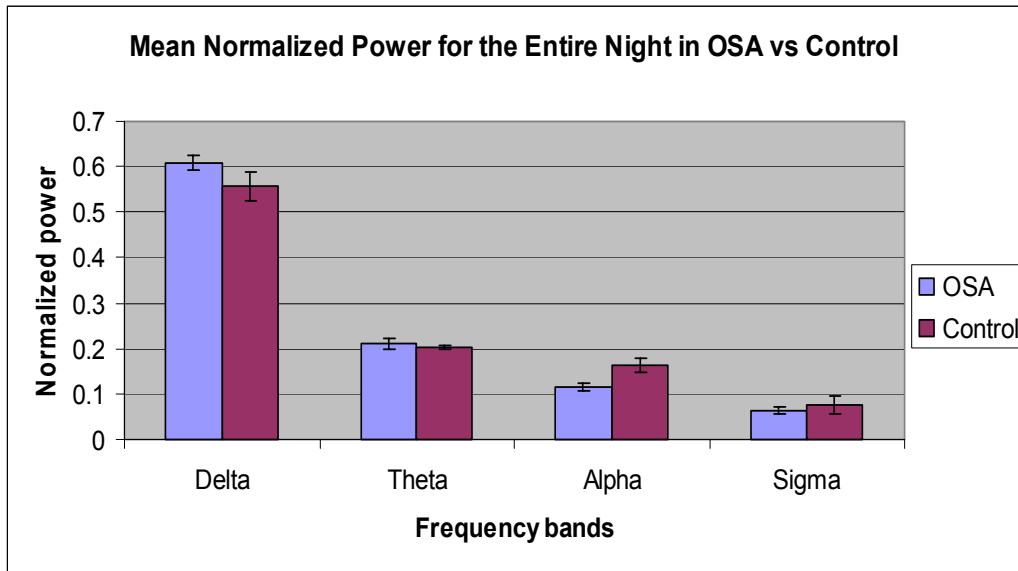
Fig 3.6 Comparison of mean normalized power for OSA vs. Control group

The mean average powers for the entire night in Delta and Theta bands were not significantly greater in OSA than in the control group using the two-sample unequal variance T-Test. The Alpha band showed a significant increase in the control group (0.0071) whereas Sigma did not show a significant increase in the control group.

3.4 Comparison of normalized power differences across sleep stage transitions and AH event terminations

In order to examine the normalized power differences across sleep stage transitions and then compare with differences observed across event terminations, EEG clips were extracted that included transitions of sleep from deeper sleep stage to lighter and similarly lighter sleep stage to deeper sleep stage. 10s of data on either side of the transition were analyzed and their differences were calculated. Eight subjects were selected randomly from the OSA group and the clips extracted. This was performed using the program *SleepStageChangeClip.m* in Matlab. To make the selection based on

probability, only 2/3 of the data clips were chosen using a random generator for each subject. The analysis was performed and the mean normalized power differences for the group are given in Fig 3.7. The results got for individual subjects are given in Appendix D, Fig 1-8. The differences did not show consistent significance across event terminations and sleep stage transitions in individual subjects.

Mean (± SD) Normalized Power Differences 10s before and after sleep stage transitions and AH event terminations for OSA (n=8)

Legend:
- Mean Transition to lighter sleep stage
- Mean Transition to deeper sleep stage
- Mean Apnea/Hypopnea event termination

X-axis: Frequency bands (Delta, Theta, Alpha, Sigma)
Y-axis: Mean normalized power differences
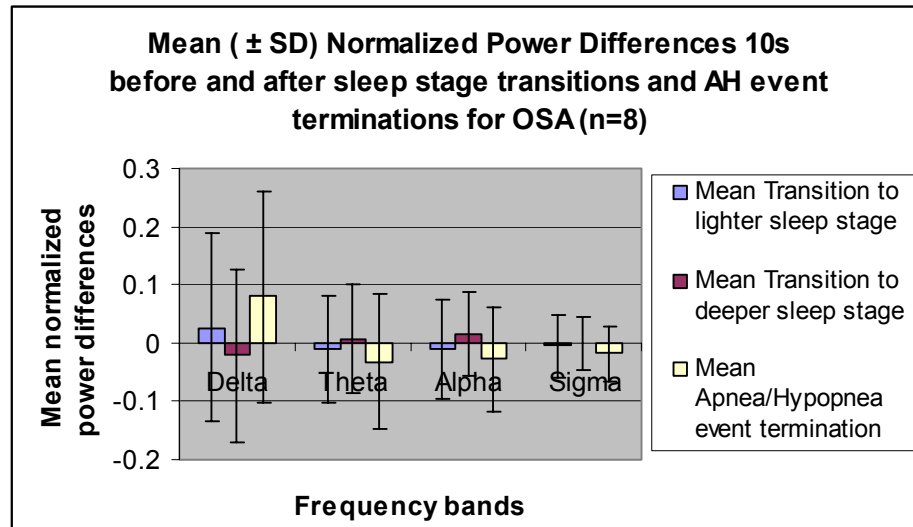
Fig 3.7 Mean Normalized power differences across sleep stage transitions and AH event terminations for OSA

3.5 Comparison of normalized power ratios across sleep stage transitions and AH event terminations

The normalized power ratios across event terminations were calculated:

$$\text{Normalized power across termination} = \frac{\text{Normalized power before termination}}{\text{Normalized power after termination}}$$

This was performed for the data set considered in Section 3.4. The results obtained after analysis of sleep stage transition and event terminations for the individual subjects are given in Appendix D, Fig 9-16. The ratios did not show significance across event terminations and sleep stage transitions.

CHAPTER 4

DISCUSSION AND LIMITATIONS

This chapter deals with the analysis of the results obtained from the preliminary study of event terminations and also the results obtained from detection of these events using power spectral analysis. It further deals with the limitations of the study.

4.1 Discussion of Power spectral analysis around event termination

The first part of the study of apneic and hypopneic event terminations (2217 apneas and hypopneas) showed that significant changes in cortical activity occurred that were detected by the EEG placement at C3/A2. These differences were calculated as the change in average normalized power of the sleep waves, 10 sec before the termination and 10 sec after the termination. Delta band (1-4 Hz) showed significant decrease (1.34E-06); Theta band (4-8 Hz) showed a significant increase (0.0002), Alpha band (8-12 Hz) also showed a significant increase (0.0001) along with a significant increase in Sigma band (12-16 Hz) (0.0007). Mean normalized Alpha power across Control subjects was significantly greater (0.0071) than that of the OSA group. These results were in agreement with the hypothesis we had formulated from literature review which stated that detectable changes in cortical activity occurred during event terminations. The delta power increase is studied to be due to an increase in inspiratory effort before the termination of the apneic/hypopneic event [16, 19, 20]. The presence of an increased

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alpha/theta/sigma activity after apnea/hypopnea indicates the occurrence of an arousal which led to the termination of the event [17].

However these results were notably different from the study performed by Dingli *et al*. [9] who had performed a similar power spectral analysis based on sleep stages. They had observed a significant decrease in theta power after event termination irrespective of the sleep stage in which the event occurred. They also observed that during REM sleep, events that did not terminate with a cortical arousal did not show significant spectral power changes. In NREM sleep they found a significant increase in delta power for non arousal terminating events. The overall theta power was significantly less for OSA subjects when compared to healthy subjects. The subject demographics were 14 males and 1 female in the study group and 4 males and 3 females in the control group. They had studied 2,596 apneas/hypopneas. They had argued the increase of delta activity after event termination, during non arousal terminating events, was due to a form of slow wave arousal. According to ASDA [10] delta bursts maybe indicants of an arousal but this indicator is unreliable without use of additional polygraphic parameters.

4.2 Discussion of detection of SDB events using power spectral analysis

The changes in power of the frequency bands, as obtained from the preliminary study, varied in their values for different event terminations and subjects. After observing the OSA group, a minimum value of power difference was chosen corresponding to each sleep wave frequency band, in order to encompass maximum number of event terminations. When these threshold values were applied to the entire

night data of the OSA group, it was observed that though the apnea and hypopnea events were detected to a good precision (r= 0.98), there were other changes, not corresponding to previous manually scored SDB events, that similarly crossed the threshold values selected. These non apneic/hypopneic power differences had similar averages as the power differences due to apneic and hypopneic event terminations as shown in Section 3.2.2.

These non apneic/hypopneic cortical changes coincided with sleep stage changes (from deeper sleep to lighter sleep 6% of the detected events and from lighter sleep to deeper sleep 4% of the detection times) and also with no sleep stage transitions (54% of the detection times) (Fig 3.4). The power differences across sleep stage transitions were compared with differences across apnea/hypopnea terminations and were not found to be significant. Hence the threshold values could not be made more specific in the order to separate sleep stage transitions from apneic/hypopneic event terminations.

4.3 Study Limitations

In accordance with the hypothesis presented in Chapter 2, the possibility of respiratory arousals terminating SDB events does prove to hold true from this investigation. However the reason for the presence of cortical changes occurring even when SDB events were not scored needs to be understood.

One explanation for this phenomenon could be the theory of Respiratory effort-related arousal (RERA) events which are defined by the American Academy of Sleep Medicine (AASM) as "*an event characterized by increasing respiratory effort of more*

than 10 sec leading to an arousal from sleep which does not fulfill the criteria for a hypopnea" [33]. Studies based on nonapneic respiratory events by Cracowski *et al.* [33] showed that among 15 subjects having moderate sleep apnea, RERA's were present to a small extent but demonstrated the same progressive increases in respiratory effort as observed in a hypopneic event termination. These RERA's corresponded to a less than 30 % decrease in airflow when compared to a decrease of flow as 50 % in hypopneas. Hence the possibility of changes in power occurring due to RERA's similar to apneic/hypopneic events needs to be investigated.

Another contributing factor to an increased number of detections could be due to transient arousals. Many sleep disorders are known to bring about transient arousals in patients which are basically brief arousals that do not alter sleep stage scoring. These arousals are known to be associated sometimes, and not always, with body movements or respiratory events [11]. This could be a possible explanation for the number of false detections during epochs of sleep which showed no stage transition in both the Control and OSA group.

As the K-complexes and spindles had not been removed from the analyzed data, the contribution of these cortical activities also needs to be considered. Sleep spindles as defined in Section 1.5 are composed of waves in the range of 7-14 Hz (high frequency) and may occur near the stage 1 to stage 2 transitions early during sleep [11]. K complexes are characterized by a negative sharp wave that is immediately followed by a positive component and occur mostly during stage 2 sleep [11]. These are high voltage slow wave activity and often seen occurring along with sleep spindles. These are also

observed to be evoked in response to auditory stimuli. These wave forms are also observed in people who do not suffer from sleep disorders and thus could be the reason for the number of events detected in the Control group.

The subjects that were studied showed a predominantly larger number of hypopneic events when compared to apneic events (2016:201). Though the study did not observe differences in the detection of apneic events vs. hypopneic events for given threshold values, this method could be further validated by analyzing a larger number of apneic events.

Thus, in order to further pursue the detection of SDB by observing changes in cortical activity, the EEG has to be identified for features like transient arousals, RERA's, K-complexes and sleep spindles in order to study the efficiency of this method.

CHAPTER 5

CONCLUSION & FUTURE WORK

From the current investigation of SDB detection, we have attempted to simplify the process of its diagnosis by using data obtained only from EEG. The results obtained from the preliminary study of 2217 apnea and hypopnea event terminations shows that there are significant changes that appear in delta, theta, alpha and sigma frequency bands of the EEG spectrum which can be used to detect apnea/hypopnea events. Earlier studies have not observed significant changes in all four sleep waves. To our knowledge this is the first time that SDB events have been studied from all night EEG data by analyzing power spectral changes that occur during an event.

However in order to increase the specificity of the detection of SDB events it would be necessary to identify the reasons for the false SDB detections and by studying whether they can be removed from the data before analysis, we can pursue this investigation further.

The possibility of observing changes in Beta frequency band (16 – 30 Hz) has been studied across apnea/hypopnea event terminations in two OSA subjects. Both subjects showed a significant increase in normalized Beta value (Appendix D, Table 9) after event termination. This can be extended to all the subjects in the future and if found significant, can also be used to indicate event terminations.

It has also been observed that addition of frontal leads to the normal EEG placement for C3 or C4 improves the detection of cortical arousals following SDB events [34]. The study observed to have an increased detection of 24% respiratory event-related arousals. Thus in order to detect cortical arousals better, data extracted from frontal leads can be implemented to study this method further.

APPENDIX A

10-20 ELECTRODE PLACEMENT OF EEG ELECTRODES

10-20 Electrode placement of EEG System
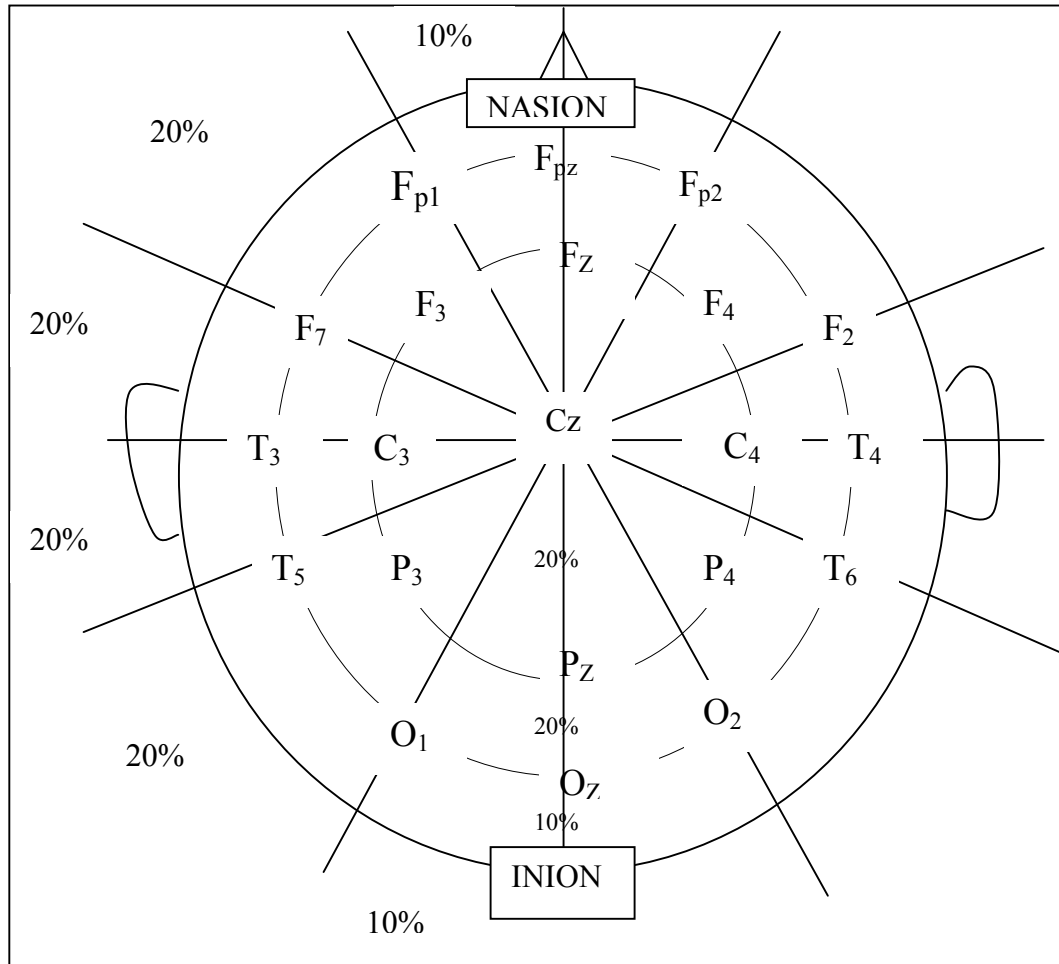
Diagram of 10-20 electrode placement [28].

The 10-20 system of electrode placement is a standard method of placing the scalp electrodes. The 10-20 refers to the 10 and 20% spacing between electrodes. It is based on the location of the electrodes and the underlying cerebral cortex. Each location is represented by a letter along with a subscript of a letter or a number. The letter represents the underlying lobe of the cerebral cortex and the subscript represents the hemisphere

location. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital. The even numbers refer to the right side of the hemisphere whereas the odd numbers refer to the left side of the hemisphere. The z refers to the midline position of the electrode placement. The Nasion is the point between the forehead and nose and Inion refers to the bump at the back of the skull [29].

APPENDIX B

FILTER DESIGN

Design of Low Pass FIR Filter

The ideal transfer function of a low pass filter is given as

$$h_D(n) = 2f_c \frac{\sin(n\omega_c)}{n\omega_c} \quad \text{for } n \neq 0$$

$$= 2f_c \quad \text{for } n=0$$

where f_c is the cut-off frequency.

The Hanning window is defined as

$$w[n] = \frac{1}{2}\left[1 + \cos\left(\frac{2\pi n}{N}\right)\right] \quad \text{for} \quad n \leq N\text{-}1/2$$

The FIR filter impulse response is then given as

$$h(n) = h_D(n)w(n)$$

For an FIR filter designed using the Hanning window the important design features are:

Transition width (Hz) = 3.1/N

Passband Ripple = 0.0546

Main lobe relative to side lobe (dB) = 31

Stopband attenuation (dB) = 44

N = 200 was found to be optimum having a transition bandwidth of 0.0155 Hz.

The cut off frequency is designed for 25 Hz and is normalized to the Nyquist frequency (half of the sampling frequency).

$$f_c = 25/50 = 0.5$$

Frequency characteristics of the FIR filter
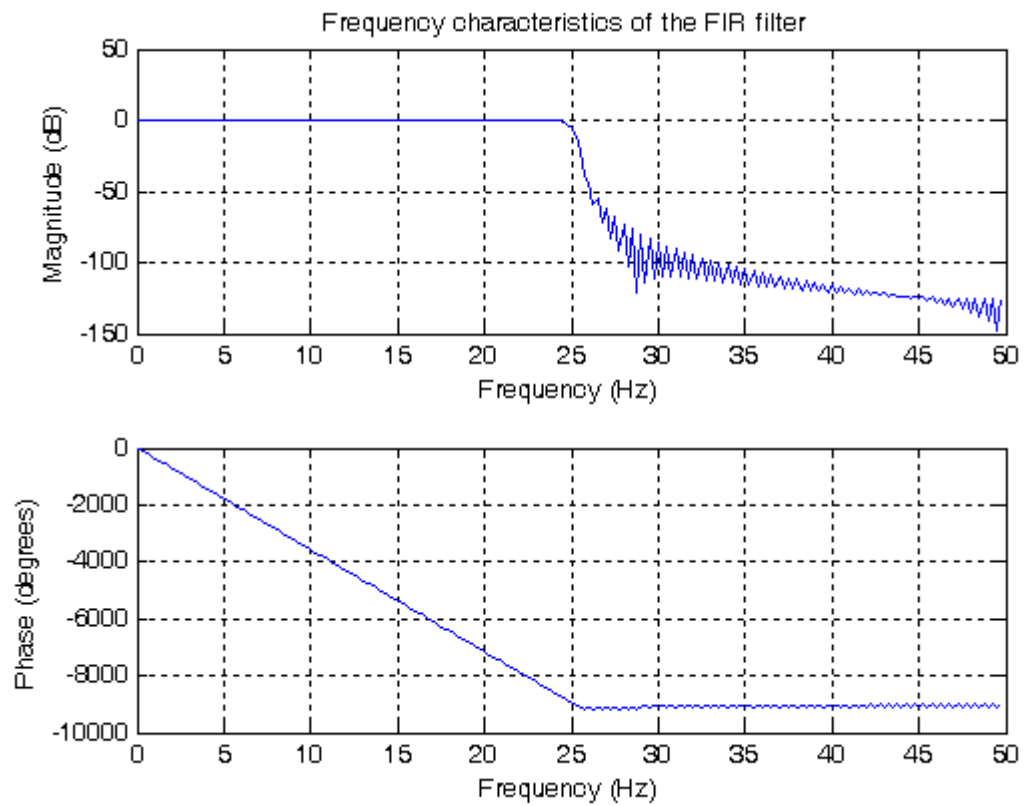
Magnitude and phase plot of filter

Implementation of Low Pass Filter using MATLAB® environment

wn=hanning(200);
fc=0.5;
hn=fir1(199,fc,wn);

APPENDIX C

ALGORITHMS USED IN THE IMPLEMENTATION
OF SDB DETECTION

Extraction of EEG data clips containing Apnea events

```matlab
%ClipFile.m
%This function is used to obtain clips containing 10 seconds of data
%before the start of the apneic event, the data spanning the entire
%duration of the event and 10 sec of data following the termination %of
the event

function [allEventsClip] = clipFile()
[Signal, Duration, SampRate, StartHH, StartMM, StartSS, Apnea] =
ReadClipApnea([], 0, 1, 1, 1, 2, 0, []);

evtNo=0; flag=0; beginEvt=1; i=1;
[r c]=size(Apnea); % Determines the size of apnea annotation got from
                        extracting the signal
while (i<=c)
   entireClip=[];
   apduration=[];
   while (Apnea(i)==1) % Checks for start of apneic event
      if(beginEvt==1)
         if((i-10)>0)
         nine_sec_prior=Signal((i-10)*100:((i-1)*100));
         else
         nine_sec_prior=Signal(1:(i-1)*100); %if less than 10s exists
         previous to this event commencement
         end
         beginEvt=2;
      end
      var =Signal((((i-1)*100)+1) :i*100);
      apduration=[apduration; var];
      i=i+1;
      flag=1;
   end

   if(beginEvt==2)
      if((i+10)<=c)
      eleven_sec_later=Signal(((((i-1)*100)+1):(((i+10)*100)-1));
      else
      eleven_sec_later=Signal((i-1)*100:end);     %if less than 10s
                                    exists after the end of the event
      end
   end
```

Extraction of EEG data clips containing Apnea events(Continued)

```
if (flag ==1)
        evtNo=evtNo+1;
        entireClip=[nine_sec_prior;apduration;eleven_sec_later];
        allEventsClip{evtNo}=entireClip;
        flag=0;
        beginEvt=1;
end
i=i+1;
end
```

Extraction of EEG data clips containing Hypopnea events

```
%ClipFile.m

%This function is used to obtain clips containing 10 seconds of data
before
%the start of the hypopneic event, the data spanning the entire
duration of the
%event and 10 sec of data following the termination of the event

function [allEventsClip] = clipFile()
[Signal, Duration, SampRate, StartHH, StartMM, StartSS, Apnea] =
ReadClipApnea([], 0, 1, 1, 1, 2, 0, []);
evtNo=0; flag=0; beginEvt=1; i=1;
[r c]=size(Apnea); % Determines the size of apnea annotation got from
                    extracting the signal
while (i<=c)
   entireClip=[];
   apduration=[];
   while (Apnea(i)==4) % Checks for start of hypopnea event
      if(beginEvt==1)
         if((i-10)>0)
         nine_sec_prior=Signal((i-10)*100:((i-1)*100));
         else
         nine_sec_prior=Signal(1:(i-1)*100); %if less than 10s exists
                                previous to this event commencement
         end
         beginEvt=2;
      end
```

Extraction of EEG data clips containing Hypopnea events (Continued)

```
    var =Signal((((i-1)*100)+1) :i*100);
    apduration=[apduration; var];
    i=i+1;
    flag=1;
  end

  if(beginEvt==2)
    if((i+10)<=c)
    eleven_sec_later=Signal(((((i-1)*100)+1):(((i+10)*100)-1));
    else
    eleven_sec_later=Signal((i-1)*100:end);%if less than 10s  exists
    after the end of the event
    end
  end

  if (flag ==1)
    evtNo=evtNo+1;
    entireClip=[nine_sec_prior;apduration;eleven_sec_later];
    allEventsClip{evtNo}=entireClip;
    flag=0;
    beginEvt=1;
  end
  i=i+1;
end
```

PSD Analysis at Event Termination

```
%PSDanalysisClipFile.m
%This program performs spectral analysis of the clips that were
extracted from ClipFile.m around the apnea/hypopnea terminations

powerSpec =dspdata.psd();
total_pwr_bEVT=[];
total_pwr_aEVT=[];

delta_pwr_bEVT=[];
theta_pwr_bEVT=[];
alpha_pwr_bEVT=[];
sigma_pwr_bEVT=[];
delta_pwr_aEVT=[];
theta_pwr_aEVT=[];
alpha_pwr_aEVT=[];
sigma_pwr_aEVT=[];

ratio_delta_bEVT=[];
ratio_theta_bEVT=[];
ratio_alpha_bEVT=[];
ratio_sigma_bEVT=[];
ratio_delta_aEVT=[];
ratio_theta_aEVT=[];
ratio_alpha_aEVT=[];
ratio_sigma_aEVT=[];

for i=1:length(allEventsClip)
  Signal=allEventsClip{i};
  [r c]=size(Signal);

  % PSD analysis for 10 s before event termination
  clipBeforeTermination=Signal((r-2000):(r-1000));
  dcfree_signal= detrend(clipBeforeTermination) ; %DC offset removal

  % zero phase digital filtering
  wn=hanning(200);
  fc=0.5;
  hn=fir1(199,fc,wn);
  filt_signal=filtfilt(hn,1,dcfree_signal);
```

```matlab
%Power Spectral Density Estimate
Hs=spectrum.welch('Hamming',128);
powerSpec(i)=psd(Hs,filt_signal,'Fs',100,'NFFT',8192)

%Calculation of average power from area under PSD curve
delta_pwr_bEVT(i)=trapz(powerSpec(i).data(82:328));
theta_pwr_bEVT(i)=trapz(powerSpec(i).data(329:656));
alpha_pwr_bEVT(i)=trapz(powerSpec(i).data(657:984));
sigma_pwr_bEVT(i)=trapz(powerSpec(i).data(985:1311));
%Normalization of frequency bands
total_pwr_bEVT(i)=trapz(powerSpec(i).data(82:1311));
ratio_delta_bEVT(i)=delta_pwr_bEVT(i)/total_pwr_bEVT(i)
ratio_theta_bEVT(i)=theta_pwr_bEVT(i)/total_pwr_bEVT(i)
ratio_alpha_bEVT(i)=alpha_pwr_bEVT(i)/total_pwr_bEVT(i)
ratio_sigma_bEVT(i)=sigma_pwr_bEVT(i)/total_pwr_bEVT(i)

% PSD analysis for 10 s after event termination
clipAfterTermination=Signal((r-1000):(r));
dcfree_signal= detrend(clipAfterTermination);
wn=hanning(200);
fc=0.5;
hn=fir1(199,fc,wn);
filt_signal=filtfilt(hn,1,dcfree_signal);

%Power Spectral Density Estimate
Hs=spectrum.welch('Hamming',128);
powerSpec(i)=psd(Hs,filt_signal,'Fs',100,'NFFT',8192)

%Calculation of average power from area under PSD curve
delta_pwr_aEVT(i)=trapz(powerSpec(i).data(82:328));
theta_pwr_aEVT(i)=trapz(powerSpec(i).data(329:656));
alpha_pwr_aEVT(i)=trapz(powerSpec(i).data(657:984));
sigma_pwr_aEVT(i)=trapz(powerSpec(i).data(985:1311));

%Normalization of frequency bands
total_pwr_aEVT(i)=trapz(powerSpec(i).data(82:1311));
ratio_delta_aEVT(i)=delta_pwr_aEVT(i)/total_pwr_aEVT(i)
ratio_theta_aEVT(i)=theta_pwr_aEVT(i)/total_pwr_aEVT(i)
ratio_alpha_aEVT(i)=alpha_pwr_aEVT(i)/total_pwr_aEVT(i)
ratio_sigma_aEVT(i)=sigma_pwr_aEVT(i)/total_pwr_aEVT(i)
end
```

Detection of events from EEG signal for the entire night duration

```
%Detection_Events_Entire_Night.m
%This program implements 2 adjacent 10s sliding windows that
%calculates differences of average power by sliding 5 s.
%It detects occurrences corresponding to event terminations. It also
% verifies if these detections coincides with previously scored events.
clear;
[Signal, Duration, SampRate, StartHH, StartMM, StartSS,Apnea,Stage]
= ReadClipApnea([],0 , 1, 1,1, 1, 0, [])

delta_pwr_before=[];
theta_pwr_before=[];
alpha_pwr_before=[];
sigma_pwr_before=[];
ratio_delta_before=[];
ratio_theta_before=[];
ratio_alpha_before=[];
ratio_sigma_before=[];

delta_pwr_after=[];
theta_pwr_after=[];
alpha_pwr_after=[];
sigma_pwr_after=[];
ratio_delta_after=[];
ratio_theta_after=[];
ratio_alpha_after=[];
ratio_sigma_after=[];


delta_diff=[];
theta_diff=[];
alpha_diff=[];
sigma_diff=[];

delta_peaks=[];
alpha_peaks=[];
theta_peaks=[];
sigma_peaks=[];
%Threshold values chosen from study
thresh_delta=0.15;
thresh_alpha=-0.045;
```

Detection of events from EEG signal for the entire night duration (Continued)

```
thresh_theta=-0.1;
thresh_sigma=-0.05;

event_count=0;

dcfree_signal=detrend(Signal); %DC offset removal

% Zero phase digital filtering
wn=hanning(200);
fc=0.5;
hn=fir1(199,fc,wn);
filt_signal=filtfilt(hn,1,dcfree_signal);

[m n]=size(filt_signal);
L=floor((m - 2000)./500);
i=0;
j=0;
 % PSD analysis for 10 s before event termination
while (i<=L)
   win_Signal= filt_signal(((500*i)+1): (1000 + (500*i)));
   i=i+1;

   Hs=spectrum.welch('Hamming',128);  %Power Spectral Density
                                       Estimate
   powerSpec_before(i)=psd(Hs,win_Signal,'Fs',100,'NFFT',8192);

   %Calculation of average power from area under PSD curve
   delta_pwr_before(i)=trapz(powerSpec_before(i).data(82:328));
   theta_pwr_before(i)=trapz(powerSpec_before(i).data(329:656));
   alpha_pwr_before(i)=trapz(powerSpec_before(i).data(657:984));
   sigma_pwr_before(i)=trapz(powerSpec_before(i).data(985:1311));

   %Normalization of frequency bands
   total_pwr_before(i)=trapz(powerSpec_before(i).data(82:1311));
   ratio_delta_before(i)=delta_pwr_before(i)/total_pwr_before(i);
   ratio_theta_before(i)=theta_pwr_before(i)/total_pwr_before(i);
   ratio_alpha_before(i)=alpha_pwr_before(i)/total_pwr_before(i);
   ratio_sigma_before(i)=sigma_pwr_before(i)/total_pwr_before(i);
end
```

```matlab
% PSD analysis for 10 s after event termination
while (j<=L)
   win_Signal= filt_signal((1001+(j*500)):(2000 +(j*500)) );
   j=j+1;
   Hs=spectrum.welch('Hamming',128);
   powerSpec_after(j)=psd(Hs,win_Signal,'Fs',100,'NFFT',8192);

   %Calculation of average power from area under PSD curve
   delta_pwr_after(j)=trapz(powerSpec_after(j).data(82:328));
   theta_pwr_after(j)=trapz(powerSpec_after(j).data(329:656));
   alpha_pwr_after(j)=trapz(powerSpec_after(j).data(657:984));
   sigma_pwr_after(j)=trapz(powerSpec_after(j).data(985:1311));

   %Normalization of frequency bands
   total_pwr_after(j)=trapz(powerSpec_after(j).data(82:1311));
   ratio_delta_after(j)=delta_pwr_after(j)/total_pwr_after(j);
   ratio_theta_after(j)=theta_pwr_after(j)/total_pwr_after(j);
   ratio_alpha_after(j)=alpha_pwr_after(j)/total_pwr_after(j);
   ratio_sigma_after(j)=sigma_pwr_after(j)/total_pwr_after(j);
end

   %Calculating differences between 2 adjacent 10s sliding windows
for m=1:L-1
   delta_diff(m)=ratio_delta_before(m)-ratio_delta_after(m);
   theta_diff(m)=ratio_theta_before(m)-ratio_theta_after(m);
   alpha_diff(m)=ratio_alpha_before(m)-ratio_alpha_after(m);
   sigma_diff(m)=ratio_sigma_before(m)-ratio_sigma_after(m);
end

   %Comparison of differences with threshold values
for m=1:L-1
   if (delta_diff(m)>thresh_delta)
      delta_peaks(m)=1;
   else
      delta_peaks(m)=0;
   end
   if(alpha_diff(m)<thresh_alpha)
      alpha_peaks(m)=1;
   else
      alpha_peaks(m)=0;
   end
```

Detection of events from EEG signal for the entire night duration (Continued)

```
if(theta_diff(m)<thresh_theta)
      theta_peaks(m)=1;
   else
   theta_peaks(m)=0;
   end
   if(sigma_diff(m)<thresh_sigma)
      sigma_peaks(m)=1;
   else
      sigma_peaks(m)=0;
   end
end
%Scoring of event terminations
   for p=1:L-1
      if((delta_peaks(p)& alpha_peaks(p)) |(delta_peaks(p)&
        theta_peaks(p))| (delta_peaks(p)& sigma_peaks(p)))

         arousal(p)=1;
         event_count=event_count+1;
         %Verifying 10 sec gap between two arousal occurances
         if((p >3)& (arousal(p-1)| arousal(p-2)))
            arousal(p)=0;
            event_count=event_count -1;
         end
      else
      arousal(p)=0;
      end
   end
% To verify scoring of events with previously scored apnea/hypopnea
events
 apneic_count=0;
 hypop_count=0;
 ap_delta=[];
 ap_alpha=[];
 ap_theta=[];
 ap_sigma=[];
 t=1;
 without_arousal=arousal;
 for n=2:L-1
     if(arousal(n)==1)
     flag=1;
```

```
        start= floor((((n+1)*500)-1199)./100); % check 12 sec before
        finish= floor((((n+1)*500)+1000)./100);%check 10 sec after
        while(start<finish & flag==1)
            start=start+1;
            if (Apnea(start)==1)
                apneic_count=apneic_count+1;
                flag=0;
                ap_delta(t)=delta_diff(n);
                ap_alpha(t)=alpha_diff(n);
                ap_theta(t)=theta_diff(n);
                ap_sigma(t)=sigma_diff(n);
                arousal(n)=0;
                t=t+1;
            end
            if (Apnea(start)==4)
                hypop_count=hypop_count+1;
                flag=0;
                ap_delta(t)=delta_diff(n);
                ap_alpha(t)=alpha_diff(n);
                ap_theta(t)=theta_diff(n);
                ap_sigma(t)=sigma_diff(n);
                arousal(n)=0;
                t=t+1;
            end
        end
    end
end

no_sleepstage_change=0;
into_deeper_sleep=0;
into_lighter_sleep=0;
wake_state=0;
noEvt_delta=[];
noEvt_alpha=[];
noEvt_theta=[];
noEvt_sigma=[];
u=1;
for q=2:L-1
    if(arousal(q))
        advance=1;
        start= floor((((q+1)*500)-999)./100);
```

Detection of events from EEG signal for the entire night duration (Continued)

```
      finish= floor(((((q+1)*500)+1000)./100);

while ((start<finish))
          if(Stage(start)<Stage(start+1))
              into_deeper_sleep=into_deeper_sleep+1;
              advance=0;
              noEvt_delta(u)=delta_diff(q);
              noEvt_alpha(u)=alpha_diff(q);
              noEvt_theta(u)=theta_diff(q);
              noEvt_sigma(u)=sigma_diff(q);
              u=u+1;
          end
          if(Stage(start)>Stage(start+1))
              into_lighter_sleep=into_lighter_sleep+1;
              advance=0;
              noEvt_delta(u)=delta_diff(q);
              noEvt_alpha(u)=alpha_diff(q);
              noEvt_theta(u)=theta_diff(q);
              noEvt_sigma(u)=sigma_diff(q);
              u=u+1;
          end
          start=start+1;
       end

       if(advance==1)
          if(Stage(finish)==0)
              wake_state=wake_state+1;
          end
          no_sleepstage_change=no_sleepstage_change+1;
          noEvt_delta(u)=delta_diff(q);
          noEvt_alpha(u)=alpha_diff(q);
          noEvt_theta(u)=theta_diff(q);
          noEvt_sigma(u)=sigma_diff(q);
          u=u+1;
       end
    end
  end
```

Power of the entire signal

```matlab
%PSD_entirenight.m
%PSD of entire data using a 10 s sliding window
[Signal, Duration, SampRate, StartHH, StartMM, StartSS] =
ReadClip([],0 , 1, 1,1, 1, 0, [])
dcfree_signal=detrend(Signal);
wn=hanning(200);
fc=0.5;
hn=fir1(199,fc,wn);
filt_signal=filtfilt(hn,1,dcfree_signal);
[m n]=size(filt_signal);

L=floor(m./1000)
x=1;
for i=1:L+1
   if i<L+1
     win_Signal= filt_signal(x:(i*1000)); %sliding the 10 s window
      x=i*1000;
   else
     win_Signal=filt_signal((L*1000):end);
   end

   [p q]=size(win_Signal);
   if p<128
       return;
   else
      Hs=spectrum.welch('Hamming',128);
      powerSpec(i)=psd(Hs,win_Signal,'Fs',100,'NFFT',8192);
      delta_pwr(i)=trapz(powerSpec(i).data(82:328));
      theta_pwr(i)=trapz(powerSpec(i).data(329:656));
      alpha_pwr(i)=trapz(powerSpec(i).data(657:984));
      sigma_pwr(i)=trapz(powerSpec(i).data(985:1311));
      total_pwr(i)=trapz(powerSpec(i).data(82:1311));
      ratio_delta(i)=delta_pwr(i)/total_pwr(i);
      ratio_theta(i)=theta_pwr(i)/total_pwr(i);
      ratio_alpha(i)=alpha_pwr(i)/total_pwr(i);
      ratio_sigma(i)=sigma_pwr(i)/total_pwr(i);
   end
 end
```

Clip data surrounding sleep transition

```matlab
%sleepStageChangeClip.m
%clip sleep stage transitions having 10s before and after transition
function [into_lighter_sleep_Clip,into_deeper_sleep_Clip] =
sleepStageChangeClip()
[Signal, Duration, SampRate, StartHH, StartMM, StartSS, Apnea,Stage]
= ReadClipApnea([], 0, 1, 1, 1, 2, 0, []);
i=10;
j=0;k=0;
[r c]=size(Apnea);
n=1;
m=1;
into_lighter_sleep_Clip=[];
into_deeper_sleep_Clip=[];
while (i<c)
    event_found_1=0;
    event_found_2=0;

    if(Stage(i)>Stage(i+1))
        j=i-9;
        while((j<=i+11)& event_found_1==0)
            if(Apnea(j)~= 10)
                event_found_1= 1;
            end
            j=j+1;
        end
        if(event_found_1==0)
            if(i+11<c)
            into_lighter_sleep=Signal(((i-9)*100):((i+11)*100));
            into_lighter_sleep_Clip{n}=into_lighter_sleep;
            n=n+1;
            end
        end
        i=i+1
    end

    if(Stage(i)<Stage(i+1))
        k=i-9;
        while((k<=i+11) & (event_found_2==0))
            if(Apnea(k)~=10)
                event_found_2=1;
            end
```

```
        k=k+1;
    end
    if(event_found_2==0)
        if(i+11<c)
        into_deeper_sleep=Signal(((k-9)*100):((k+11)*100));
        into_deeper_sleep_Clip{m}=into_deeper_sleep;
        m=m+1;
        end
    end
    i=i+1
end

i=i+1;
end
end
```

APPENDIX D

EEG PROCCESSED DATA FOR SDB DETECTION

Table 1 SDB detection from the entire night data in OSA Group

		Manual Scoring parameters				Number of normalized power differences crossing the set threshold				
OSA	AHI	Irregular respiratory events	Sleep Stage Shifts	Number of Events scored manually (Apnea/Hypopnea)	Number of SDB events detected using the Algorithm	Detection during occurrence of apnea	Detection during occurrence of Hypopneas	Detection during Stage changes from Deeper to Lighter sleep	Detection during Stage changes from Lighter to Deeper sleep	Detection during no stage transition
Subj#1	9	55	228	3/35	436	4	42	45	21	324
Subj#3	4	28	178	0/26	468	0	31	31	23	383
Subj#10	19	120	267	0/112	324	0	96	38	19	171
Subj#20	70	488	248	120/335	453	105	233	8	8	92
Subj#23	57	329	268	24/269	469	19	269	17	10	127
Subj#24	8	45	198	3/30	304	1	40	29	22	212
Subj#25	37	239	268	1/235	507	2	212	23	17	253
Subj#26	20	401	226	34/367	543	33	361	14	8	127
Subj#27	62	137	153	14/101	460	10	102	19	15	314
Subj#28	14	89	305	0/88	653	0	115	77	57	404
Subj#29	4	25	244	0/25	653	0	32	66	45	510
Subj#30	30	212	243	1/211	512	1	199	27	20	271
Subj#31	38	189	223	1/182	399	1	182	20	13	183

Table 2 SDB detection from the entire night data in Control Group

		Manual Scoring parameters				Distribution of SDB events during the night				
Control	AHI	Irregular respiratory events	Sleep Stage Shifts	Number of Events scored manually (Apnea/Hypopnea)	Number of SDB events detected using the Algorithm	Detection during occurrence of apnea	Detection during occurrence of Hypopneas	Detection during Stage changes from Deeper to Lighter sleep	Detection during Stage changes from Lighter to Deeper sleep	Detection during no stage transition
Subj#4	3	13	107	0/11	304	0	8	16	19	261
Subj#5	6	17	105	1/16	276	1	14	4	16	241
Subj#6	2	12	302	1/4	530	0	4	67	40	419
Subj#7	0	2	202	0/2	559	0	1	43	30	485
Subj#9	2	9	130	0/8	288	0	9	19	9	253
Subj#11	4	22	124	0/7	572	0	9	42	31	490
Subj#12	6	48	230	4/18	502	3	32	40	56	370
Subj#13	2	10	211	1/7	502	1	8	57	32	403
Subj#14	1	5	133	0/0	394	0	0	32	17	344
Subj#15	0	2	135	0/2	383	0	0	31	21	330
Subj#16	6	44	355	5/37	582	7	38	91	57	434
Subj#18	2	5	94	0/4	13	0	0	0	0	13
Subj#19	3	15	212	0/15	366	0	20	39	24	283
Subj#21	11	62	222	1/56	325	1	43	34	23	224

Table 3 Correlation between Number of SDB events detected and the sum of irregular respiratory events and sleep stage shifts for 13 OSA subjects

OSA	
Irregular Respiratory events + sleep stage shifts	Number of SDB events detected using the Algorithm
283	436
206	468
387	324
736	453
597	469
243	304
507	507
627	543
290	460
394	653
269	653
455	512
412	399
correlation coefficient(r)	0.114

Table 4 Correlation between Number of SDB events detected and the sum of irregular respiratory events and sleep stage shifts for 14 Control subjects

Control	
Irregular Respiratory events + sleep stage shift	Number of events detected using the Algorithm
120	304
122	276
314	530
204	559
139	288
146	572
278	502
221	502
138	394
137	383
399	582
99	13
227	366
284	325
correlation coefficient(r)	0.6032

Table 5 Correlation between number of events scored manually and automatically in OSA subjects (n=13)

OSA	Number of Events scored manually (Apnea/Hypopnea)	Number of Events scored automatically (Apnea/Hypopnea)
Subj#1	38	46
Subj#3	26	31
Subj#10	112	96
Subj#20	454	338
Subj#23	293	288
Subj#24	33	41
Subj#25	236	214
Subj#26	400	394
Subj#27	115	112
Subj#28	88	115
Subj#29	25	32
Subj#30	212	200
Subj#31	183	183
correlation coefficient(r)	0.98	

Table 6 Correlation between number of events scored manually and automatically in Control subjects (n=14)

Control	Number of Events scored manually (Apnea/Hypopnea)	Number of Events scored automatically (Apnea/Hypopnea)
Subj#4	11	8
Subj#5	17	15
Subj#6	5	4
Subj#7	2	1
Subj#9	8	9
Subj#11	7	9
Subj#12	22	35
Subj#13	8	9
Subj#14	0	0
Subj#15	2	0
Subj#16	42	45
Subj#18	4	0
Subj#19	15	20
Subj#21	57	44
correlation coefficient(r)	0.94	

Table 7 Mean Normalized Differences of Power for epochs corresponding to true SDB detection vs. false detection.

OSA	False Detection					True Detection			
	Delta	Theta	Alpha	Sigma		Delta	Theta	Alpha	Sigma
Subj#1	0.2404	-0.0922	-0.0588	-0.0886		0.2380	-0.0976	-0.0685	-0.0712
Subj#3	0.2240	-0.0599	-0.0388	-0.1248		0.2179	-0.0238	-0.0224	-0.1713
Subj#10	0.2329	-0.0605	-0.0665	-0.1051		0.2414	-0.0656	-0.0756	-0.0994
Subj#20	0.2429	-0.0895	-0.0466	-0.1060		0.2481	-0.0778	-0.0676	-0.1022
Subj#23	0.2107	-0.0559	-0.0183	-0.1358		0.2406	-0.0549	-0.0154	-0.1695
Subj#24	0.2141	-0.0613	-0.0426	-0.1094		0.2610	-0.0681	-0.0654	-0.1265
Subj#25	0.2330	-0.0821	-0.0203	-0.1299		0.2329	-0.0863	-0.0301	-0.1158
Subj#26	0.2409	-0.0657	-0.0311	-0.1429		0.2490	-0.0548	-0.0224	-0.1707
Subj#27	0.2170	-0.0758	-0.0265	-0.1139		0.2458	-0.0739	-0.0315	-0.1394
Subj#28	0.2553	-0.1405	-0.0743	-0.0398		0.2458	-0.1274	-0.0812	-0.0365
Subj#29	0.2346	-0.0628	-0.0915	-0.0796		0.2414	-0.0663	-0.0958	-0.0786
Subj#30	0.2318	-0.0814	-0.0452	-0.1044		0.2333	-0.0887	-0.0451	-0.0988
Subj#31	0.2441	-0.1205	-0.0404	-0.0825		0.2526	-0.1397	-0.0364	-0.0760
Mean ± SEM	0.2324 ±0.0036	-0.0806 ±0.0071	-0.0462 ±0.0060	-0.1048 ±0.0077		0.2421 ±0.0106	-0.0788 ±0.0306	-0.0506 ±0.0263	-0.1120 ±0.0423
T-TEST	0.0482	0.8729	0.6490	0.6143					

Table 8 Comparison of Total mean normalized power for the entire night

	OSA					Control			
	Delta	Theta	Alpha	Sigma		Delta	Theta	Alpha	Sigma
Subj#1	0.6477	0.1717	0.1057	0.0733	Subj#4	0.6297	0.1868	0.1198	0.0619
Subj#3	0.5682	0.2671	0.1054	0.0574	Subj#5	0.4724	0.1956	0.2746	0.0556
Subj#10	0.7045	0.1764	0.0641	0.0535	Subj#6	0.5680	0.2101	0.1600	0.0600
Subj#20	0.5868	0.2242	0.1202	0.0670	Subj#7	0.5180	0.2001	0.2303	0.0496
Subj#23	0.5650	0.2877	0.1062	0.0394	Subj#9	0.6016	0.2070	0.1233	0.0663
Subj#24	0.6775	0.1928	0.0781	0.0500	Subj#11	0.6075	0.1720	0.1635	0.0554
Subj#25	0.4997	0.2611	0.1755	0.0618	Subj#12	0.6234	0.2123	0.1158	0.0467
Subj#26	0.6400	0.2350	0.0835	0.0398	Subj#13	0.6197	0.2028	0.1140	0.0620
Subj#27	0.6805	0.1815	0.0996	0.0368	Subj#14	0.5772	0.2334	0.1380	0.0494
Subj#28	0.5669	0.1601	0.1777	0.0937	Subj#15	0.6317	0.1988	0.1333	0.0346
Subj#29	0.6052	0.1636	0.1088	0.1209	Subj#16	0.5865	0.2156	0.1565	0.0398
Subj#30	0.5931	0.2123	0.1264	0.0663	Subj#18	0.1590	0.2358	0.2894	0.3134
Subj#31	0.5835	0.2068	0.1446	0.0634	Subj#19	0.5960	0.1613	0.1614	0.0794
					Subj#21	0.6006	0.2057	0.1166	0.0754
Mean ± SEM	0.6091 ±0.0160	0.2108 ±0.0116	0.1151 ±0.0095	0.0633 ± 0.0065	Mean ± SEM	0.5565 ± 0.0328	0.2027 ± 0.0054	0.1640 ± 0.0157	0.0750 ±0.0186
T-TEST (p-value)	0.0830	0.2676	0.0071	0.2814					
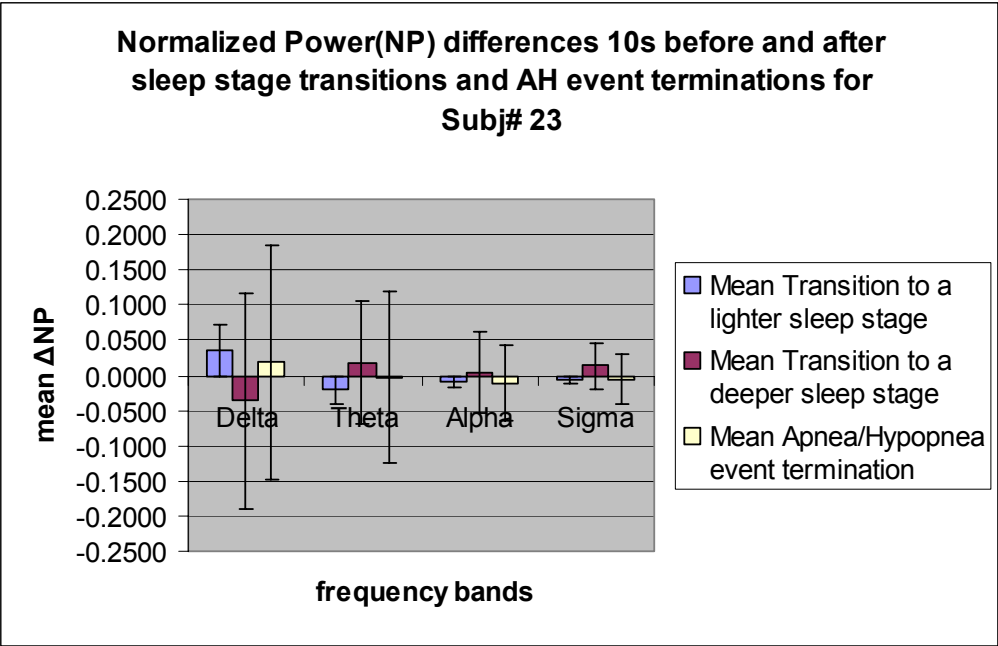
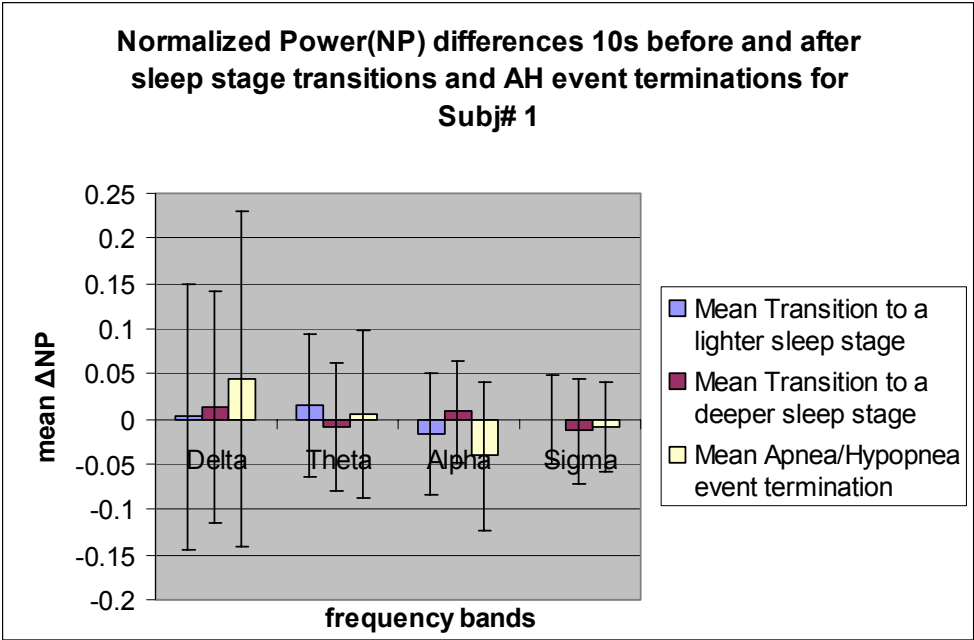Fig 1 NP differences across transitions in Subj#23

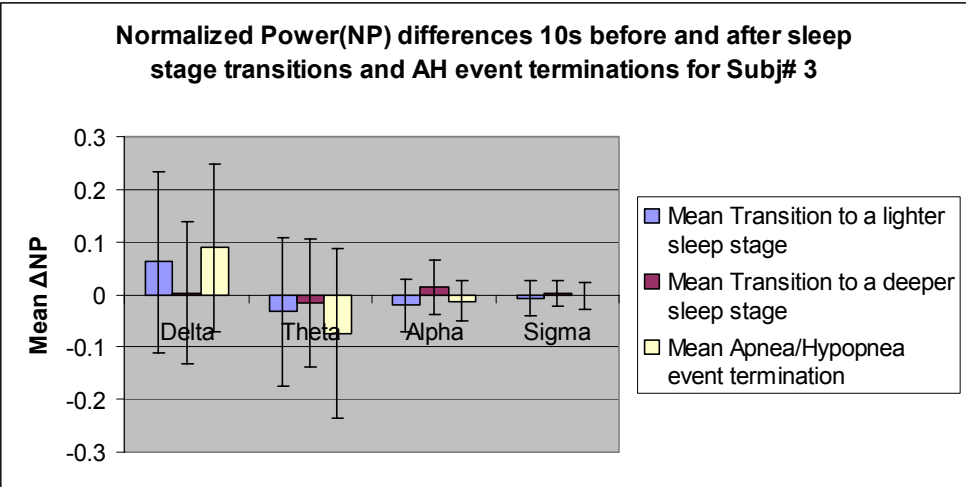Fig 2 NP differences across transitions in Subj# 1

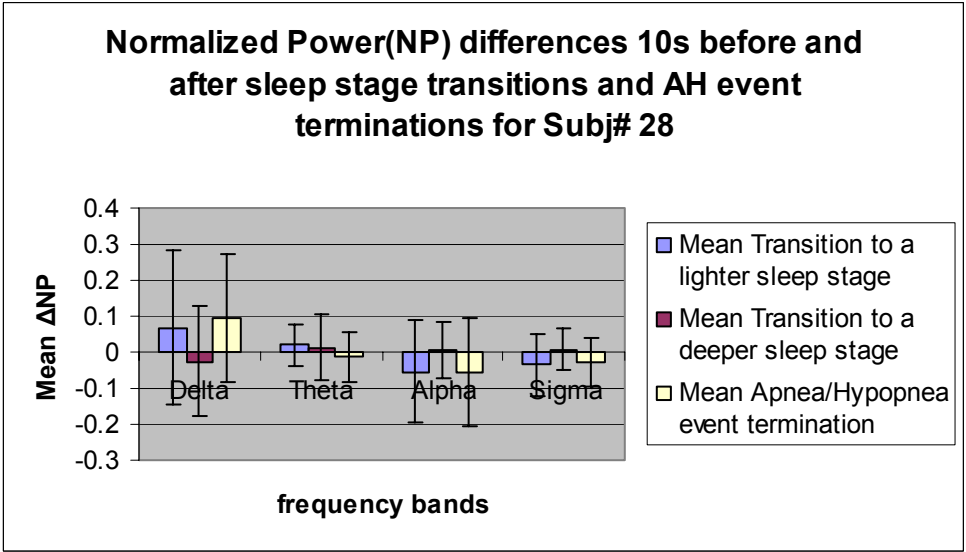Fig 3 NP differences across transitions in Subj#3

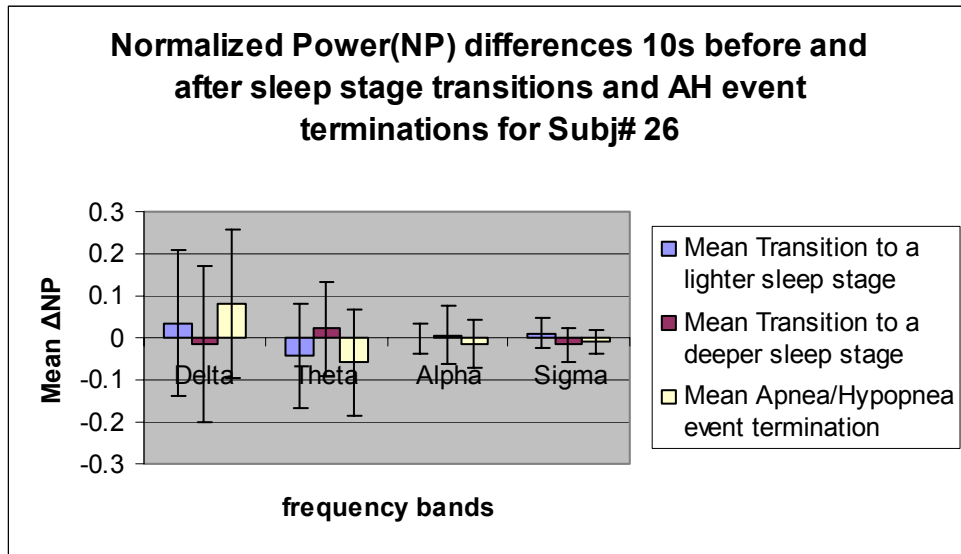Fig 4 NP differences across transitions in Subj#28

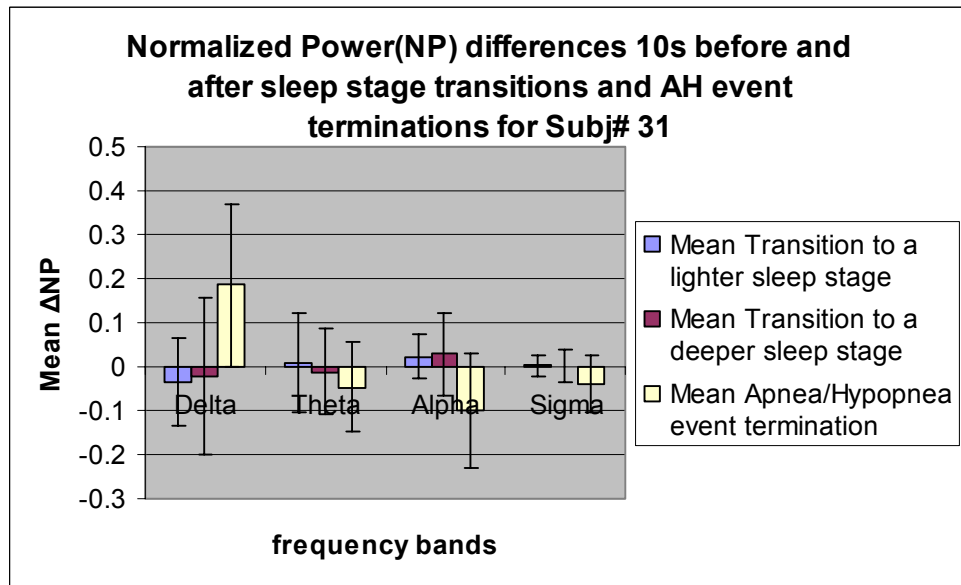Fig 5 NP differences across transitions in Subj#26
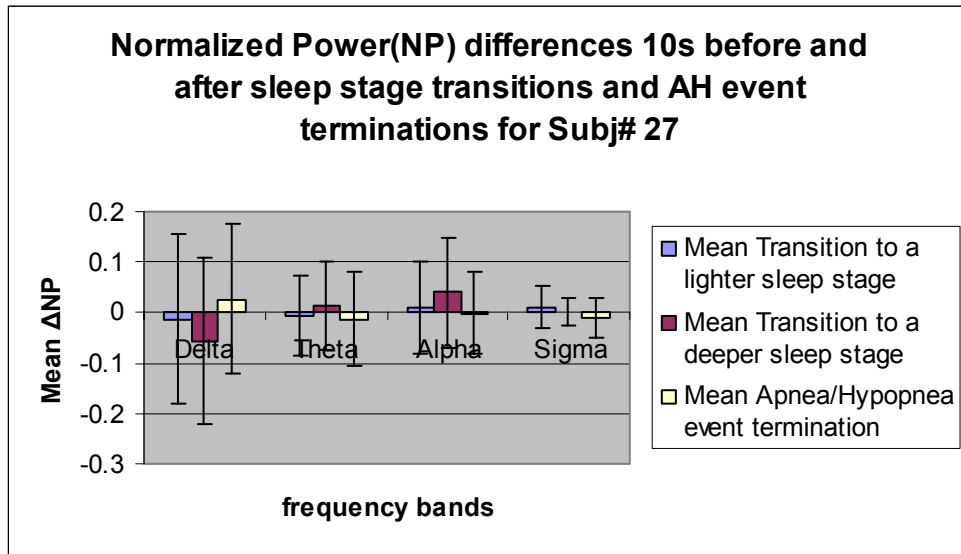

Fig 6 NP differences across transitions in Subj#31

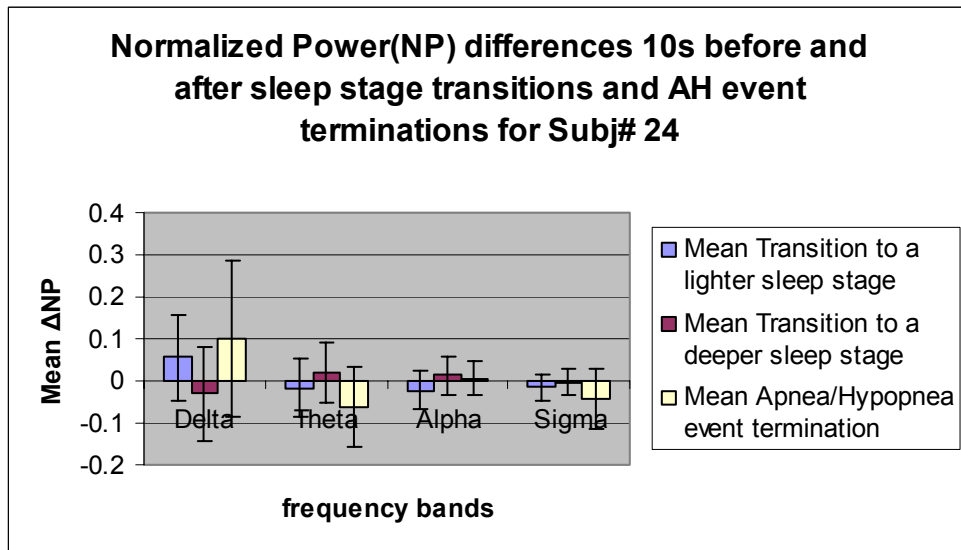Fig 7 NP differences across transitions in Subj#27
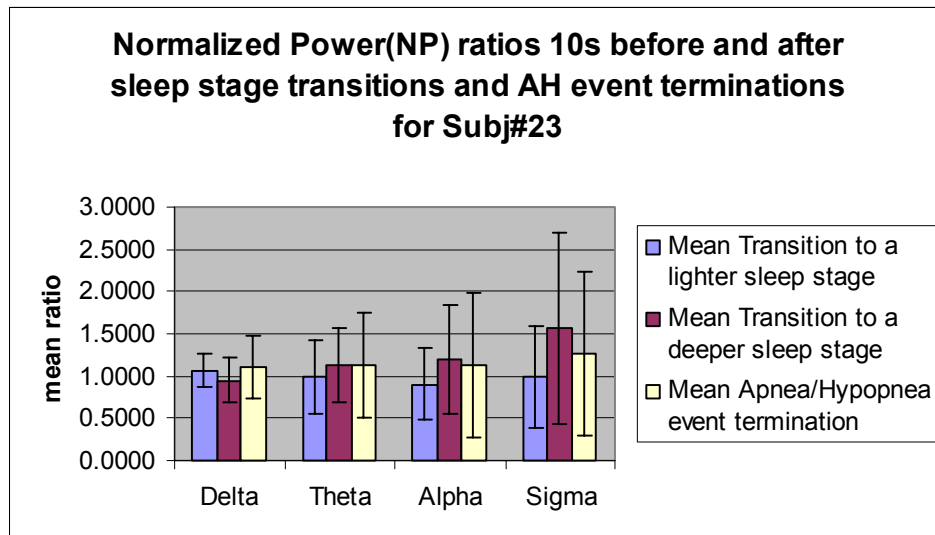

Fig 8 NP differences across transitions in Subj#24
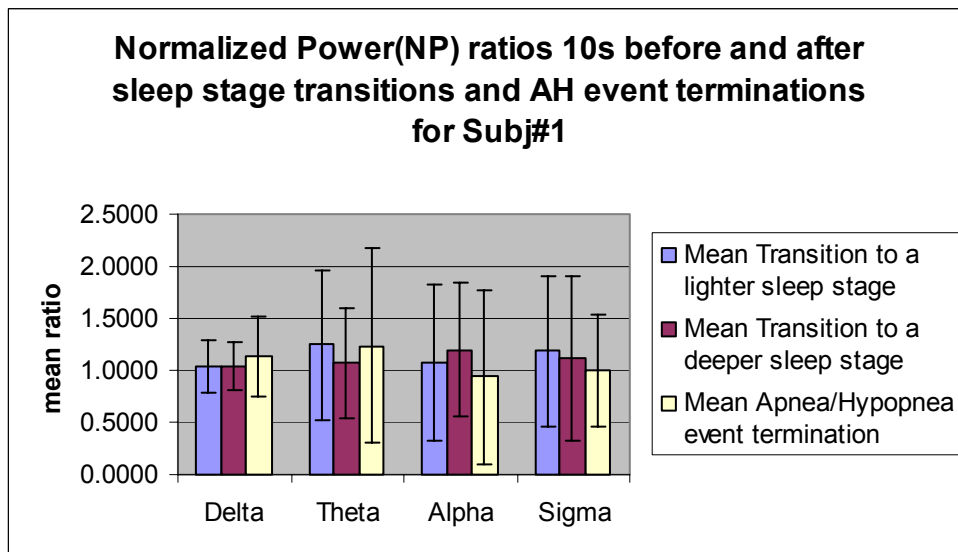
Fig 9 NP ratios across transitions in Subj#23

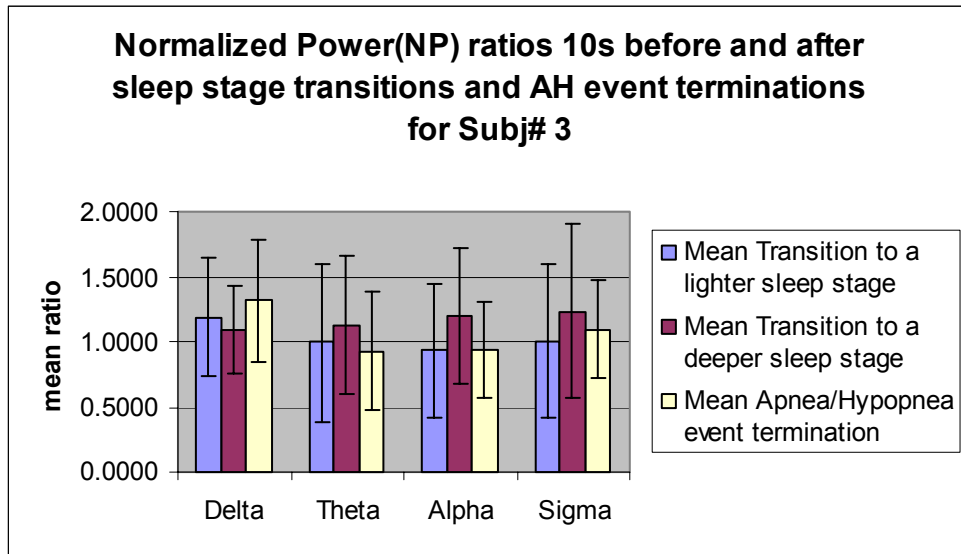Fig 10 NP ratios across transitions in Subj#1
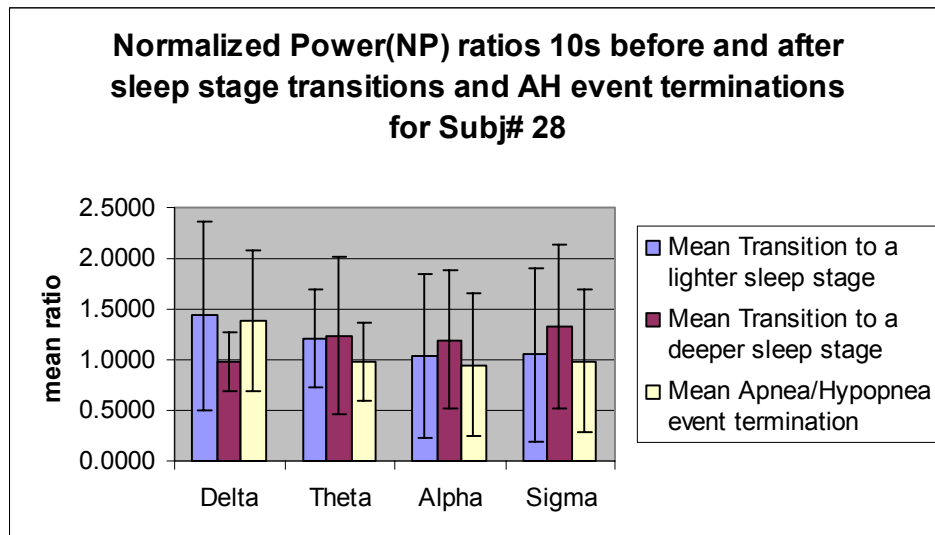
Fig 11 NP ratios across transitions in Subj#3

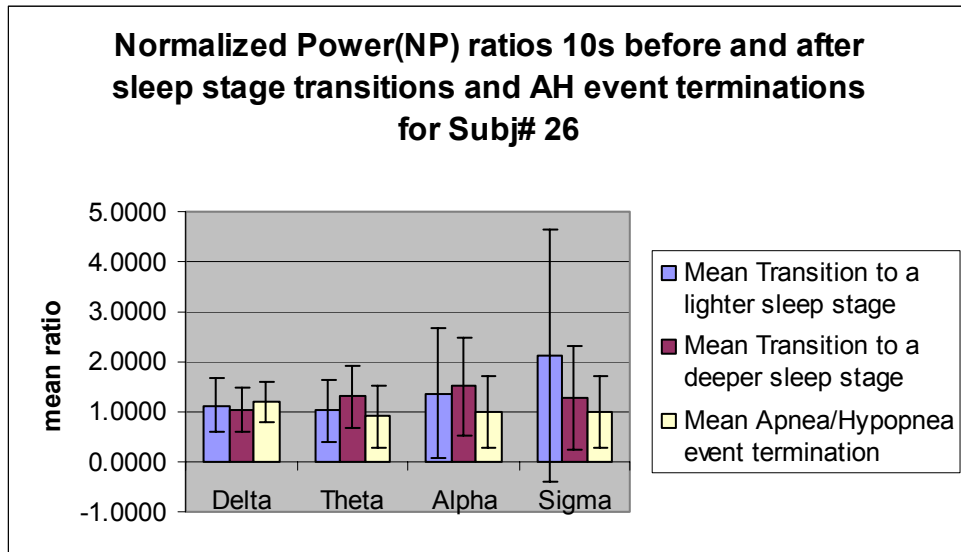Fig 12 NP ratios across transitions in Subj#28

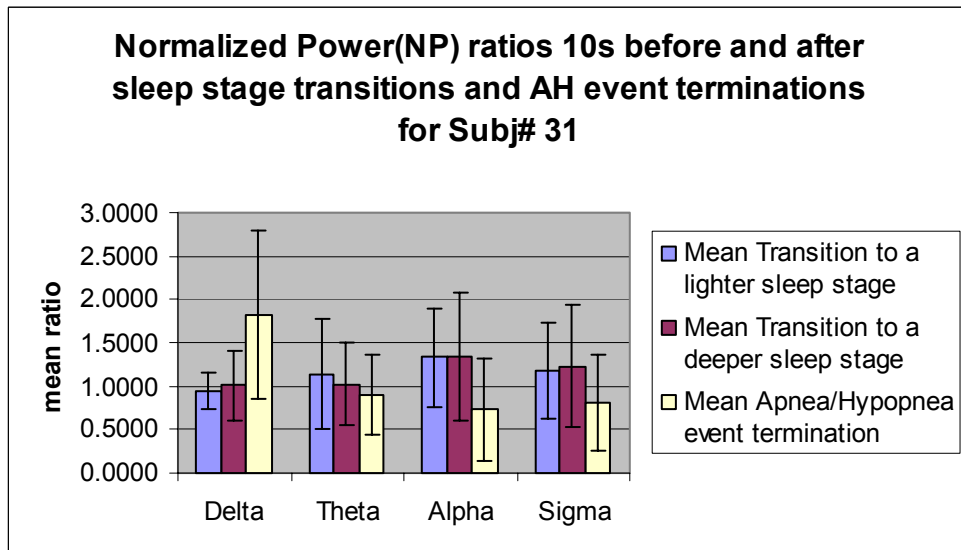Fig 13 NP ratios across transitions in Subj#26

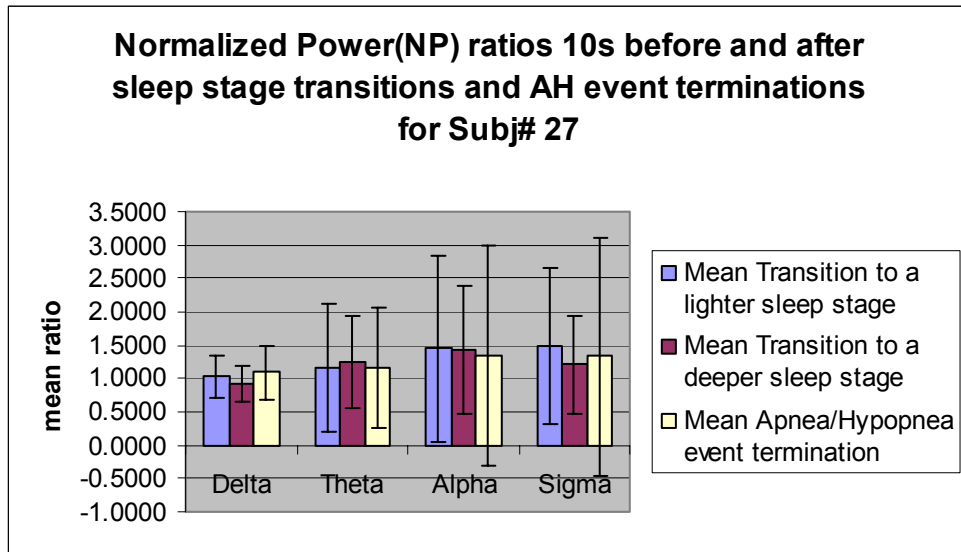Fig 14 NP ratios across transitions in Subj#31
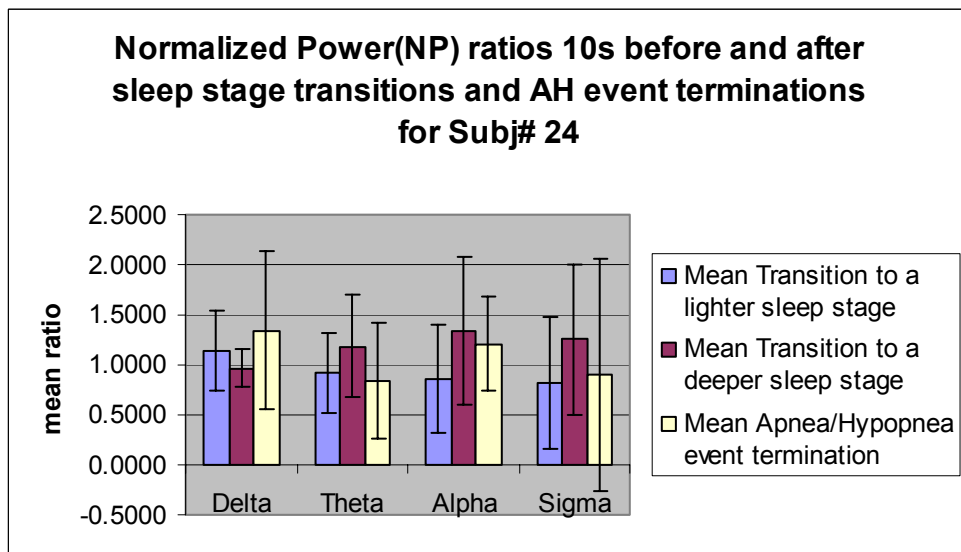
Fig 15 NP ratios across transitions in Subj#27

Fig 16 NP ratios across transitions in Subj#24

Table 9 Difference in Normalized power across event terminations

	10s BEFORE EVENT TERMINATION				
OSA	Delta	Theta	Alpha	Sigma	Beta
Subj#25	0.4359	0.2540	0.1699	0.0596	0.0789
Subj#26	0.6971	0.1821	0.0617	0.0254	0.0322

	10S AFTER EVENT TERMINATION				
	Delta	Theta	Alpha	Sigma	Beta
Subj#25	0.3987	0.2644	0.1790	0.0630	0.0931
Subj#26	0.5941	0.2354	0.0749	0.0329	0.0610

Intra Subject Variability using t-Test comparison (p-value)

	Delta	Theta	Alpha	Sigma	Beta
Subj#25	0.0002	0.0625	0.0337	0.0274	0.0057
Subj#26	3.49E-28	8.25E-17	2.83E-08	1.17E-09	1.91E-15

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BIOGRAPHICAL INFORMATION

Priya Xavier was born on April 29th 1981 in Bangalore, India. She completed her degree in Bachelors of Engineering in Electronics and Communication from Bangalore, India in 2003. In order to pursue her interest in the biomedical field, she joined the University of Texas at Arlington in fall 2004. Her research interests lie in Biomedical Signal Processing and Medical Instrumentation. She hopes to pursue these interests further in a research oriented organization working in the biomedical field.