Exacerbation in Obstructive Sleep Apnea: Early Detection and Monitoring Using a Single Channel EEG with Quadratic Discriminant Analysis *

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Abstract— **Exacerbation monitoring of obstructive sleep apnea (OSA) is important for the evaluation of treatment effectiveness and tracking the disease progression. In this study, we investigate the use of spectral features from a single channel electroencephalography (EEG) for early detection and monitoring of OSA exacerbation using the Sleep Health Heart Study dataset. We have explored 22 features at different sleep stages corresponding to different frequency bands to distinguish 410 subjects in the stable and exacerbation groups. An optimal set of 15 features has been selected using the recursive feature elimination technique. It has been found that these features provide significant discriminative information (p-value ≤ 0.05) for classification. On the test dataset of 82 EEG records, a classification accuracy, sensitivity, and specificity of 79.17%, 80.85%, and 76.00%, respectively, have been achieved using Quadratic Discriminant Analysis classifier. Results demonstrate that OSA exacerbation can be detected early and monitored with this simple yet effective method using a single channel EEG.**

I. Introduction

On an average, 22% of men and 17% of women suffer from obstructive sleep apnea (OSA) [1]. Insufficient sleep, drowsiness, and daytime sleepiness are some of the direct consequences of OSA. Untreated OSA is either responsible or strongly correlated with many diseases such as myocardial infarction, hypertension, high blood pressure, and depression [1]. OSA is not persistent for the whole duration of sleep; rather it appears in a repetitive manner as events. OSA event is associated with physiological changes such as heart rate, oxygen saturation level, and respiration. American Academy of Sleep Medicine (AASM) Taskforce defined an apnea/hypopnea event as a complete cessation or transitory reduction of breathing when the airflow decreases by more than 50% from the amplitude of baseline and the oxygen saturation level decrease by at least 4% and the event persists for a minimum of 10 seconds [2]. OSA diagnosis and severity assessment is currently measured using polysomnogram (PSG), a comprehensive test that collects different types of physiological signals including ECG, EEG, SpO_2, leg movement, body movement, and respiration. These tests are usually conducted in sleep laboratory settings and scored by certified sleep clinicians.

Although patients diagnosed with OSA are generally treated with continuous positive airway pressure (CPAP) device, many patients are not comfortable with CPAP and, in some cases, CPAP may lead to other complicacy such as dry mouth, discomfort breathing, and development of central sleep apnea. For patients with mild OSA, the use of CPAP may not provide significant improvement [3]. Oral appliance (OA) and surgical operations are possible alternative to CPAP in the management of OSA [4]. Some researchers have evaluated the effectiveness of weight reduction in the early stages of OSA [5]. One of the major challenges involved in the management of OSA is the evaluation of treatment effectiveness on a regular basis. Although CPAP is generally equipped with a system for monitoring AHI, other approaches require PSG or separate arrangements for monitoring OSA progression.

Many studies have been conducted to diagnose OSA using Electrocardiogram (ECG), pulse oximetry and electroencephalography (EEG) features [6]. Liu *et al.* proposed a neural network method for the detection of obstructive sleep apnea from EEG [7]. Almuhammadi *et al.* proposed an efficient method for sleep apnea classification based on EEG signals [8]. However, these investigations are limited to the classification of apneic subjects from healthy subjects and do not address the issue of continuous monitoring of an OSA patient for the evaluation of treatment effectiveness. In this study, we have investigated the spectral band powers of EEG signal and variance in power for the detection of OSA exacerbation and continuous monitoring of OSA at home environment with a large dataset.

II. Materials and Methods

A. Dataset

We have used the Sleep Health Heart Study (SHHS) dataset available from National Sleep Research Resource [9]. SHHS was implemented as a multi-center cohort study in two phases by the National Heart Lung & Blood Institute. Subjects were recruited in 12 centers located all over the country. In total 6441 subjects were enrolled in the first phase called SHHS-1. In the second phase of study (SHHS-2) 3295 subjects were enrolled. In both the phases Polysomnograms were obtained in an unattended setting, usually in the homes of the participants, by trained and

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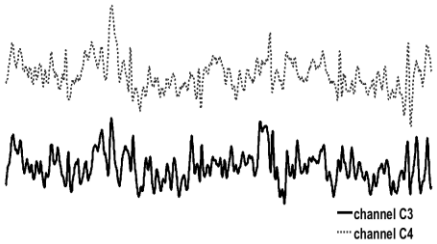

Fig. 1 Representative EEG data from channels C3-A1 and C4-A2.

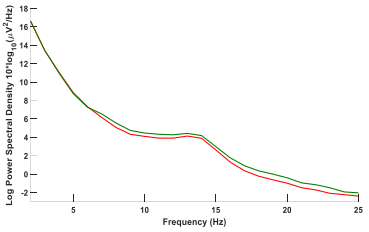

Fig. 2. EEG power spectral density of a subject from channels C3 (green) and C4 (red).

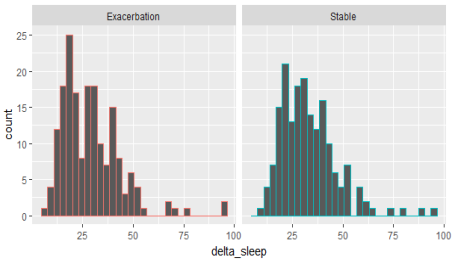

Fig. 3 Distribution of delta sleep power in exacerbation and stable OSA subjects

Certified technicians. The PSG data was saved in European Data Format (EDF). Data processing and initial scoring was done by Compumedics software [9]. Two manual scoring was included to annotate the dataset with AHI, respiratory disturbance index, sleep stages, event start and end time identification etc. In our study, we have primarily considered only those patients who were enrolled in both SHHS-1 and SHHS-2. Based on the annotated obstructive apnea-hyponea index (OAHI), we have identified 205 subjects who showed an exacerbation in their disease. In this context, exacerbation means that they have advanced to a higher severity stage or their apnea-hypopnea index (AHI) has increased by 10 scores. These 205 patients included in the exacerbation group consist of both men and women. Most of them were married and elderly and predominantly overweight or obese. To have a balanced dataset, in our study we have also included 205 non-exacerbating i.e. stable subjects. In total 410 subjects from the SHHS have been included and randomized in this study.

B. Sleep Stages and EEG Frequency Bands

In general, overnight sleep can be divided into two stages Rapid Eye Movement (REM) sleep and Non-rapid eye movement (N-REM) sleep. N-REM sleep is further divided into Stage 1, Stage 2, Stage 3, and Stage 4, where Stage 1 is the lightest sleep and Stage 4 is the deepest sleep. REM sleep is divided into Phasic and Tonic sleep. There is a cyclic pattern in the sleep where a person starts with NREM Stage 1 after sleep onset and gradually progress to Stage 4 and then again comeback to Stage 1 and then REM sleep [10]. In the whole night, 5-6 sleep cycles are typically observed with longer sleep cycles in the initial hours and shorter sleep cycles at the end. EEG signal consists of six major frequency bands namely Alpha (α), Beta (β), Gamma (γ), Delta (δ), Theta (Θ), and Sigma (σ). The details of EEG frequency bands have been provided in Table I. Previous studies have confirmed that Alpha band power activity corresponds to wakefulness, Delta and Theta band power are prevalent in NREM stage 4 and comparatively low in REM sleep [11]. During REM sleep, a mixed frequency theta including some alpha waves without sleep spindles are observed.

TABLE I. EEG FREQUENCY BANDS

Band	Delta	Theta	Alpha	Sigma	Beta	Gamma
Freq-uency	0.5 - 4	4-8	8-13	12-14	13-30	36-90

TABLE II. LIST OF SPECTRAL FEATURES

Frequency Band	**Features**
Delta	Total Power, REM Sleep Power, NREM Sleep Power
Theta	Total Power, REM Sleep Power, NREM Sleep Power
Alpha	Total Power, REM Sleep Power, NREM Sleep Power
Beta	Total Power, REM Sleep Power, NREM Sleep Power
Gamma	Total Power, REM Sleep Power, NREM Sleep Power
Slow Sigma	Total Power, REM Sleep Power, NREM Sleep Power
Fast sigma	Total Power, REM Sleep Power, NREM Sleep Power

C. Feature Extraction, Feature Selection, and Classification

The EEG signal was collected using two channels from the central region of brain for over 5 hours. One of the channel is C4-A1 and the other one is C3-A2. The sampling rate for EEG was 125 samples per second (sps). A representative portion of the raw EEG signal for a SHHS subject from the two EEG channels has been shown in Fig. 1. The power spectral densities, as shown in Fig. 2, for these two channels are very similar. In our study, we have only used the signal from C4 channel as it has been designated as primary EEG channel in SHHS. EEG spectral analysis was performed using the SpectralTrainFig App in MATLAB [9]. We have extracted 21 features from the decontaminated EEG signal as shown in Table. II. In addition, we have considered the variance in power as another feature. For plotting the Power Spectral Density (PSD) and time-frequency analysis, we have used EEGLab [12]. The distribution of data in both groups are skewed for all the variables. The distribution for delta sleep has been visualized in Fig. 3, which shows a right skewed distribution. Since the data failed normality test (Shapiro-Wilk) for all the variables, we have adopted non-parametric methods of statistical analyses i.e., Mann-Whitney U test and Wilcoxon signed rank test for testing if there is a significant difference. Sigma plot and IBM SPSS software has been used for statistical analysis. For feature selection, we have used recursive feature elimination technique using R caret package, which tune the model on the training set using all predictors, calculate model performance, calculate variable importance, and determine the appropriate number of predictors [13]. The feature extraction and classification method has been shown in Fig.4. For classification, we have used Quadratic Discriminant Analysis (QDA) classifier. The data set was divided in training and test set in an 80% and 20% ratio. Five-fold cross validation was used in the training set.

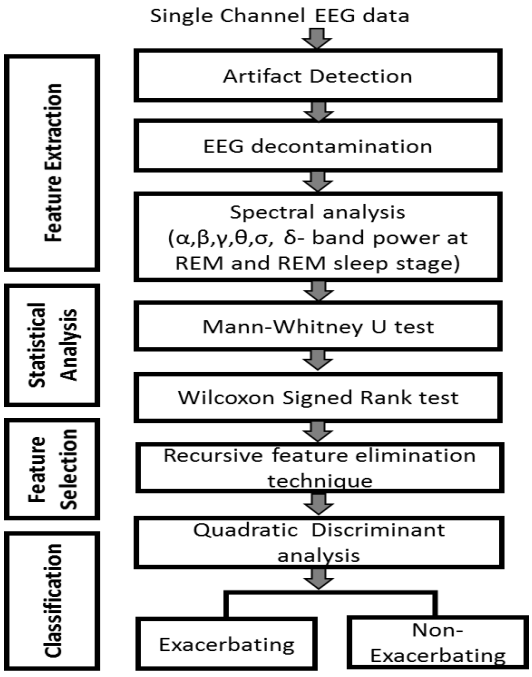

Fig. 4 Feature extraction and classification method

The QDA classifier has a non-linear decision boundary and belongs to the family of Bayesian classifiers. The quadratic discriminant function is given by,
$\delta_k(x) = -12log|\Sigma_k| - 12(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k) + log\pi_k$, where Σ_k is the covariance matrix for each class k= 1,2,….K and the classification rule is $G(x)=\arg\max_k \delta_k(x)$.

III. RESULTS

The results of Mann Whitney U test for comparing the EEG spectral features of exacerbating OSA group with non-exacerbating subjects (control group) has been shown in Table III. The significant differences (p-value < 0.05) are indicated with asterisks. The non-exacerbating group has a higher delta sleep power compared to the exacerbating group as shown in Fig. 5. In addition, the alpha band power in REM stage is higher in exacerbating group compared to non-exacerbating group. These conform to the fact that an exacerbating person spend less time in deep sleep (stage 3-4). Significant differences are also observed in beta and sigma band power.

TABLE III. RESULTS OF MANN WHITNEY U TEST

Feature	Non-Exacerbating *Median (IQR)*	Exacerbating *Median (IQR)*	*p-value*
	N = 205	N = 205	
Delta sleep	**30.563 (19.184)**	**26.094 (19.018)**	**0.000***
Delta NREM	**36.028 (22.390)**	**29.092 (21.178)**	**0.000***
Delta REM	**11.819 (6.135)**	**10.376 (6.092)**	**0.049***
Theta sleep	7.085 (4.498)	6.682 (5.498)	0.300
Theta NREM	7.925 (5.310)	7.249 (5.864)	0.070
Theta REM	4.270 (2.814)	4.244 (3.304)	0.933
Alpha sleep	3.562 (3.299)	3.557 (2.846)	0.749
Alpha NREM	3.898 (3.513)	3.751 (3.022)	0.225
Alpha REM	**2.042 (1.704)**	**2.496 (1.988)**	**0.019***
Sigma sleep	1.823 (1.213)	1.780 (1.234)	0.277
Sigma NREM	**1.978 (1.365)**	**1.843 (1.409)**	**0.037***
Sigma REM	**1.067 (0.812)**	**1.220 (0.917)**	**0.017***
Beta sleep	**0.645 (0.379)**	**0.730 (0.491)**	**0.005***
Beta NREM	**0.640 (0.350)**	**0.725 (0.477)**	**0.002***
Beta REM	**0.615 (0.451)**	**0.708 (0.539)**	**0.034***
Power Variance	**90.45 (112.33)**	**65.56 (98.62)**	**0.007***

Fig. 6 shows the time frequency analysis of the EEG of a subject showing exacerbation. Fig. 6A and Fig. 6B shows the spectrogram before and after exacerbation respectively. It can be noted from the time frequency analysis that there is a decrease in Delta band power due to exacerbation.

The results of Wilcoxon-Signed Rank test reveal a significant change within the group due to exacerbation. The spectral power in different sleep stages during baseline and follow-up visits has been shown in Fig. 7. Based on Wilcoxon signed rank test, significant changes have been marked with asterisks. Although some of the spectral features show a significant change due to aging and is observed in both the groups, some other features show a significant change for the exacerbation group only. It is noted that due to exacerbation, there is a decrease in Delta REM power and Beta N-REM power while an increase in Theta N-REM power. Alpha and sigma band power are only affected by aging.

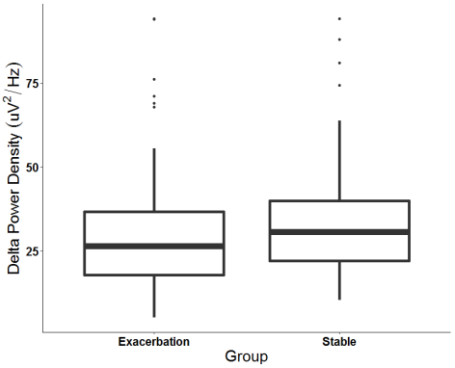

Fig.5 Boxplot for delta sleep power density

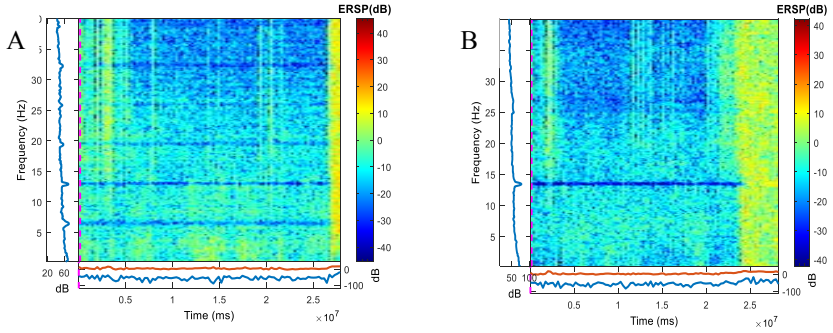

Fig. 6: Time-frequency analysis of a subject showing progression in OSA for (A) baseline EEG (B) follow-up EEG after Exacerbation.

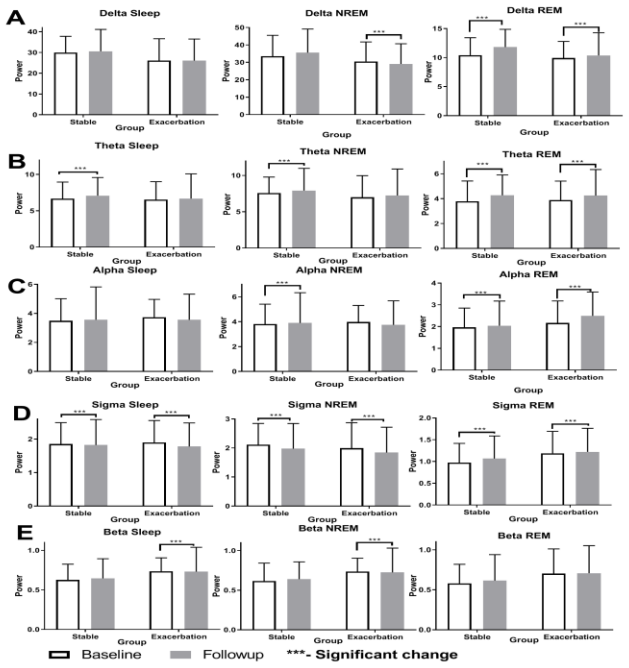

Fig. 7: Changes in EEG Spectral Power in A) Delta B) Theta C) Alpha D) Sigma E) Beta bands due to exacerbation.

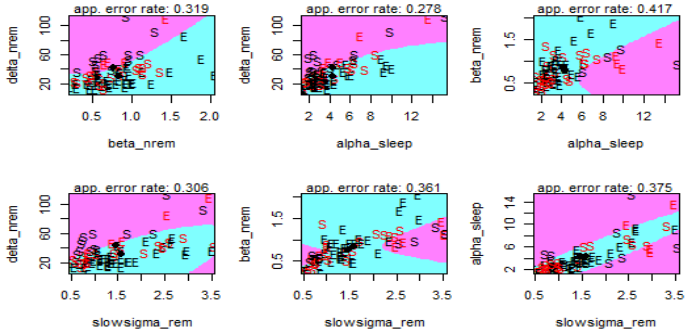

Fig. 8: Representative partition plots with extracted features

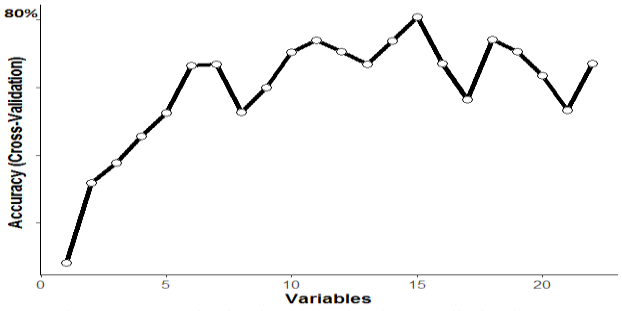

Fig. 9 Feature selection by Recursive feature elimination

The partition plot with some features are shown in Fig. 8. As shown in Fig. 9, the RFE method suggested 15 features as best predictors to achieve maximum accuracy. With the top 15 features, QDA classification achieved an accuracy of 77.06%, sensitivity of 75.19%, and specificity of 78.05% in the training set. In the test set, it achieved an accuracy of 79.17%, sensitivity of 80.85% and specificity of 76%. These results are summarized in Table IV.

TABLE. IV FIVE-FOLD CROSS VALIDATION RESULTS OF THE QDA CLASSIFICATION MODEL

Data set	Exacerbation Classification		
	Accuracy	*Sensitivity*	*Specificity*
Training	77.06%	75.19%	78.05%
Test	79.17%	80.85%	76.00%

IV. CONCLUSION

This study indicates that EEG spectral power in different sleep stages can show a significant difference between exacerbating and non-exacerbating subjects. In addition, there is a significant change in spectral features due to a progression in the disease. The classification results achieved with quadratic discriminant analysis is promising and has the potential for further improvement. The use of single channel EEG data enables the use of this method on wearable devices. This study also reveals that spectral features of single channel EEG obtained from central aerial position alters for healthy and apneic subjects in different sleep stages. This demonstrates the potential of using EEG spectral features for early detection and continuous monitoring of OSA. These in turn can be utilized to monitor effectiveness of OSA treatment and home management of OSA.

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