

Identification of Obstructive Sleep Apnea from Normal Subjects: FFT Approaches Wavelets

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Abstract

An FFT-based algorithm for Obstructive Sleep Apnea (OSA) patient identification using R-R interval (RRI) data is investigated. The identification is done on the whole record as OSA patient or non-patient (normal). The power spectral density of the three main bands of the RRI data is computed and then three identification factors are calculated from their ratios. The first identification factor is the ratio of the PSD of the low-frequency (LF) band to that of the high-frequency (HF) band. The second identification factor is the ratio of the PSD of the very low-frequency (VLF) band to that of the low-frequency (LF) band, while the third identification factor is the ratio of the PSD of the very low-frequency (VF) band to that of the high-frequency (HF) band. The RRI data used in this work were drawn from MIT database. The three identification factors are tested on MIT trial data. The best factor, which is the (VLF/LF) PSD ratio, is then tested on MIT test data and to evaluate the performance of the identification. The efficiency of identification approaches 87%. The method is then improved by applying FFT on short records and averaging the results to get an efficiency of 93%. Another improvement was done by zero-padding the short records to double its size and then averaging the results to get an efficiency of 93%. This efficiency is compared with a previous work on the same purpose using wavelets which resulted in 90% accuracy.

Keywords: Obstructive Sleep Apnea, Non-Invasive Diagnosis, Identification, Spectral Analysis, FFT, Wavelets

1. INTRODUCTION

Sleep apnea is a common sleep disorder that is defined as a complete or partial cessation of breathing during sleep [1].

Obstructive sleep apnea (OSA) is the common form of apnea that occurs when the upper airway is completely or partially obstructed due to the relaxation of dilating muscles. Hypoapnea occurs when the airway is partially collapsed and causes 50% reduction of air accompanied by oxygen desaturation of 4% or greater [2]. The severity of apnea is measured by a commonly used standard such as the apnea/hypoapnea index (AHI), which is the number of apnea and hypoapnea events per hour [1]. Most clinicians regard an apnea index below 5 as normal, and an apnea index of 10 or more as pathologic.

In the general population, the greatest challenge for primary care providers lies in determining which patients with some symptoms such as snoring warrant further evaluation, as most patients with OSA snore, but most snorers do not have OSA [3]. In developed countries the cost of investigating these symptoms has increased considerably during the last decade as the only reliable method for the diagnosis of OSA until now is overnight sleep studies (Polysomnography) [4], which is a cumbersome, time consuming and expensive procedure requiring specially trained polysomnographers and needs recording of EEG, EOG, EMG, ECG, nasal air respiratory effort and oxygen saturation [1].

Therefore, it is of a great importance and interest to have automatic screening algorithms on a single-lead ECG signals. This will reduce the pressure on sleep laboratories and make it possible to diagnose sleep apnea inexpensively from ECG recordings acquired in the patient's home.

Heart rate variability (HRV) is referred to as the beat-to-beat variation in heart rate. Instantaneous heart rate is measured as the time in seconds between peaks of two consecutive R waves of the ECG signal. This time is referred to as the RRI. The variation of heart rate accompanies the variation of several physiological activities such as breathing, thermoregulation and blood pressure changes [5]. HRV is a result of continuous alteration of the autonomic neural regulation of the heart i.e. the variation of the balance between sympathetic and parasympathetic neural activity. The increase of sympathetic tone or decrease of parasympathetic activity will increase heart rate [5]. Theoretically, in OSA the cessation of breathing will cause the respiration center in the brain to activate its autonomic components (sympathetic and parasympathetic) which send feed back impulses to the heart to compensate for the lack of O₂ and low blood pressure. This interaction between the heart and the brain is reflected into the beat-to-beat variation of heart rate. Therefore the analysis of HRV in time-domain or in frequency-domain should somehow reveal the variations in breathing.

Frequency-domain analysis approaches use one of the signal transformations such as FFT, STFT, wavelet transform to estimate the power spectral density of the RRI data. The frequency spectrum of the RRI data is divided into three main bands:

- The very low-frequency band (VLF): $f \in (0.0033 - 0.04) \text{ Hz}$
- The low-frequency band (LF): $f \in (0.04 - 0.15) \text{ Hz}$
- The high-frequency band (HF): $f \in (0.15 - 0.4) \text{ Hz}$

The LF component reflects the sympathetic tone in heart regulation, while the HF component reflects the parasympathetic tone and is also related to the frequency of respiration [6]. The ratio LF/HF describes the balance between sympathetic and parasympathetic neural activity. However the physiological background of the VLF component is not well known but is proposed to be associated with thermoregulation, vasomotor activity, or the rennin-angiotensin system [7].

The LF/HF ratio has been used by some researchers to represent the sympathetic modulation of the heart rate, however this interpretation is not universally accepted. A major limitation of applying the HF component is that it is highly sensitive to differences in ventilation and breathing pattern within and across individuals [8].

In OSA patients, the respiratory modulation of heart rate is not confined to within-breath changes but also takes the form of large cyclical variations that correlate with the episodic apneas. These oscillations generally fall into the VLF band (between 0.01 and 0.04 Hz) [9].

The FFT is used as identification tool of OSA within an efficiency of 87% using the (VLF/LF) PSD ratio as an identification factor on whole records of MIT data [10]. In this work, this technique is improved by applying it on short records and averaging the results for final accuracy. Another improvement is also done by zero-padding the short records and applying the FFT on longer records and averaging for finding the final accuracy.

2. MATERIAL AND METHODS

2.1. Data Description

The ECG data used in this work were taken from the MIT data base [11]. The data contain 30 trial records and 30 test records. These data sets are single channel ECGs that were extracted from polysomnographic recordings with a sampling rate of 100 Hz for an average duration of 8 hours. The sleep recordings originated from 32 subjects (25 men and 7 women) between 27 and 63 years of age, with weight between 53 and 135 kg. Recordings from 17 of the 32 subjects were represented in the trial set and in the test set; eight subjects were only in the test set, and the remaining seven subjects were only in the trail set. The duration of the recordings varied between 401 and 578 min (average: 492, standard deviation: 32 min).

A total of 40 OSA records and 20 normal records were used in this study. MIT-trial records were used to setup the screen algorithm, which is then applied to the MIT-test records. The ECG data sets are listed in Table 1.

Data	OSA Records	Normal Records
MIT Trial	20	10
MIT Test	20	10

TABLE 1. ECG Data Sets

2.2. Pre-Processing of Data

2.2.1 QRS Detection

The accuracy of the identification algorithm depends primarily on the accuracy of the (QRS) detection (R peak detector) that is used to obtain the RRI signal from the raw ECG data. The QRS detection and beat classification (normal or not) is accomplished by the single-lead threshold based ECG wave boundaries detector "Ecgpuwave", which is available on the physionet website [12]. The raw RRI data used in this work are the Normal-to-Normal (NN) intervals obtained directly from the QRS detector without any smoothing and filtering steps; therefore it could contain false intervals, missed and/or ectopic beats.

2.2.2 Outliers Removing and Resampling

The simple approach that is used to exclude false RRI is to bound the RRI with lower and upper limits of 0.4 and 2 seconds respectively [9]. Therefore all RRI samples beyond these limits are excluded. Further removal of outliers is achieved by using of a sliding 41-points moving average filter (MAF) as follows: A local mean is computed for every 41 consecutive RRI excluding the

central interval. The output of the MAF is used as a reference measure to reject or accept the central RRI. If the central RRI is within 20% of the computed local mean, then it is qualified as true RRI otherwise it is an outlier and excluded from the RRI data. Re-sampling at 1 Hz and estimation of missed value are intended to generate equally spaced RRI [13].

3. IMPLEMENTATION AND RESULTS

3.1 Evaluation Measures

A classifier is a parameter or a variable, with a suitable optimal threshold, that is used in a classification algorithm. In this study, only binary classification is considered, e.g. classification between two different cases, positive (OSA) and negative cases (normal). The performance of a classifier is evaluated by three main metrics: Specificity, Sensitivity and Accuracy as follows [14]:

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) * 100 \quad (1)$$

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) * 100 \quad (2)$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{TN} + \text{FN}) * 100 \quad (3)$$

Where the entities in the above equation are defined in confusion matrix shown in Table 2, and T is the total number of data under test.

Actual Class ^a	Predicted Class ^a	
	Positive (P)	Negative (N)
Positive (P)	TP	FN
Negative (N)	FP	TN

^aPositive = OSA, Negative = Normal, T=True, F=False

TABLE 2. The Confusion Matrix

Sensitivity represents the ability of a classifier to detect the positive cases, i.e. OSA cases. Specificity indicates the ability of a classifier to detect negative cases, e.g. normal cases. Accuracy represents the overall performance of a classifier. It indicates the percentage of correctly classified positive and negative cases from the total number of cases.

3.1 FFT Results on long records

The FFT is applied on the whole record of each subject in the trial data. The PSD of the three main bands is found by summing the corresponding FFT results for the different bands. The PSD of the VLF band is taken from 0 to 0.03 Hz, while the PSD of the LF band and the HF band is selected as (0.03 to 0.15 Hz) and (0.15 to 0.4 Hz) respectively. The three identification factors are computed then from the calculated PSD values.

Figures (1-3) show the result of the 3 identification factors on MIT-trial data. The results of identification are shown on Table 3. The metrics used in Table 3 are the sensitivity [14] (accuracy

of identification of apnea cases), and the specificity [14] (accuracy of identification of normal cases) and the efficiency (accuracy of identification of all cases). It is to be concluded from Table 1 that the VLF/LF identification factor is better than the other two factors. The same algorithm is applied using the VLF/LF identification factor with the same threshold on the MIT-test data and results in 16/20 sensitivity and 10/10 specificity and total accuracy of 26/30. Fig.4 shows these results.

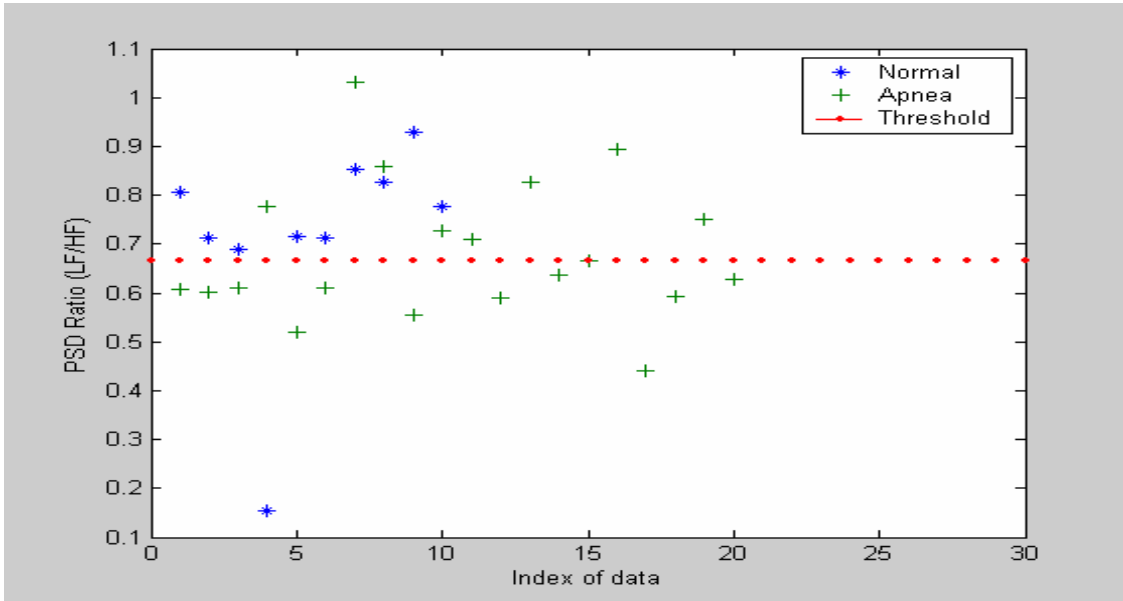


FIGURE 1: (LF/HF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using FFT on Long Record

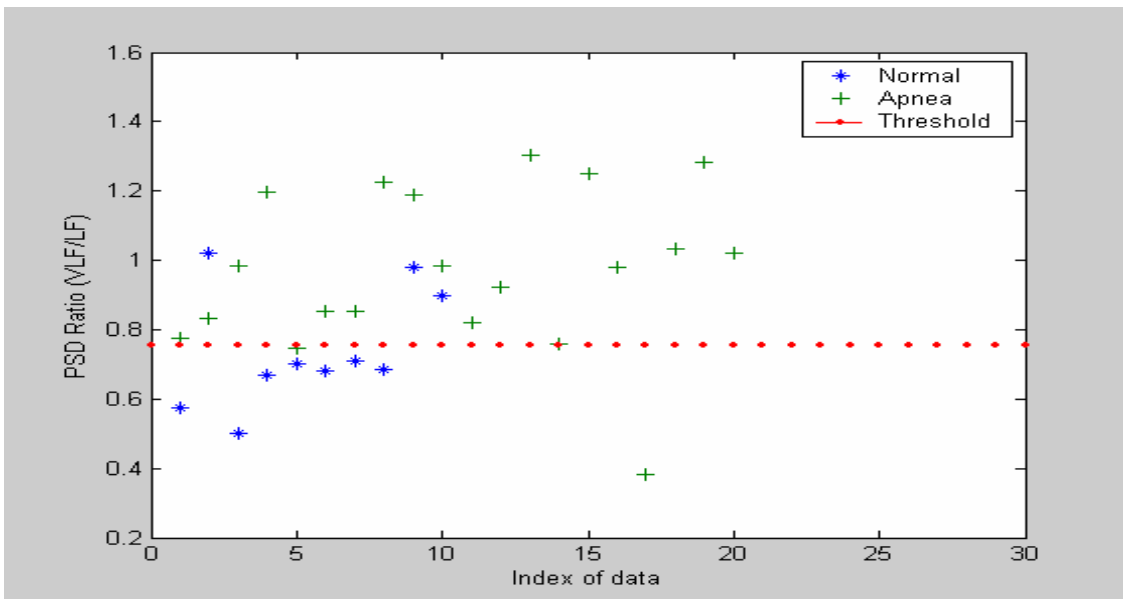


FIGURE 2: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using FFT on Long Record

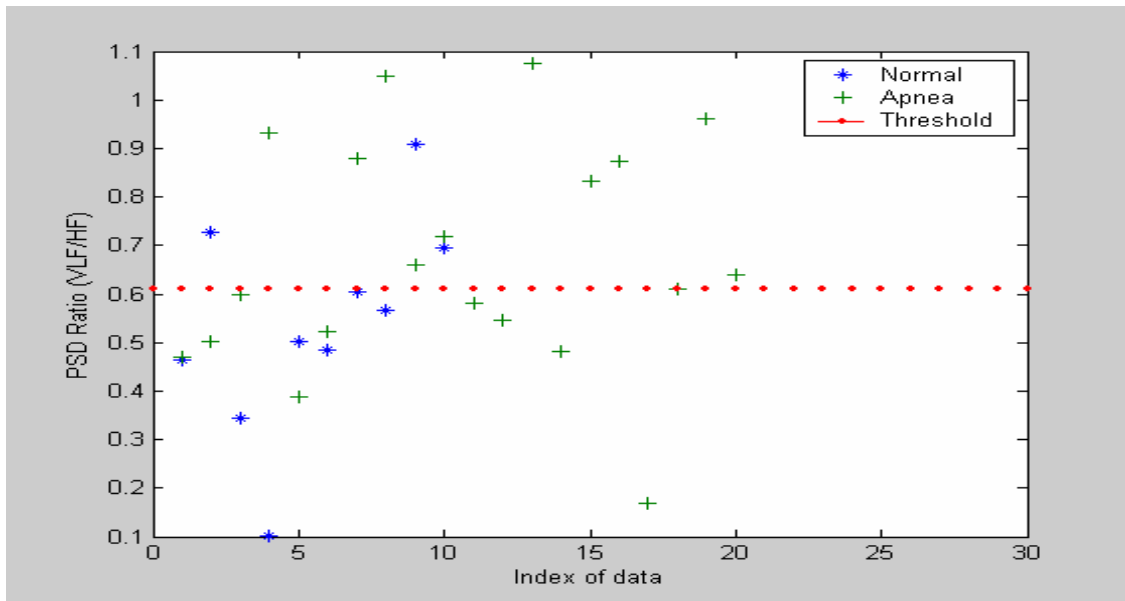


FIGURE 3: (VLF/HF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using FFT on Long Record

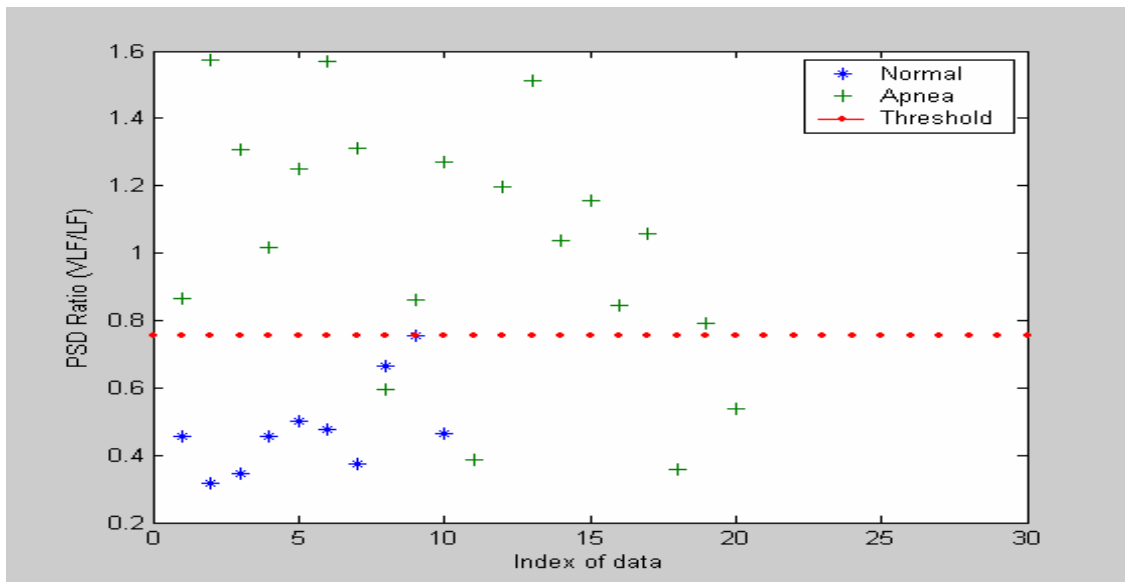


FIGURE 4: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-test Data using FFT on Long Record

Identification factor	Specificity	Sensitivity	Accuracy	Threshold
LF/HF	9/10	12/20	21/30	0.666
VLF/LF	7/10	18/20	25/30	0.756
VLF/HF	7/10	11/20	18/30	0.61

TABLE 3: Different Results on MIT-Trial Data

3.2 Wavelet Results

A soft decision algorithm for approximate power spectral density estimation for Obstructive Sleep Apnea (OSA) patient classification using R-R interval (RRI) data is investigated in [15]. This algorithm is based on fast and approximate estimation of the entropy (simply logarithmic value of PSD) of the wavelet-decomposed bands of the RRI data. The classification is done on the whole record as OSA patient or non-patient (normal). This technique classifies correctly 28/30 of MIT-test data using Haar wavelet filters [15]. In order to compare the FFT results with wavelet results, the wavelet results are listed in Figures 5 and 6 for both trial and test data. See Table 4 for brief results.

Data	Specificity	Sensitivity	Accuracy
MIT-Trial	7/10	20/20	27/30
MIT-Test	8/10	20/20	28/30

TABLE 4: Different Results using Wavalets

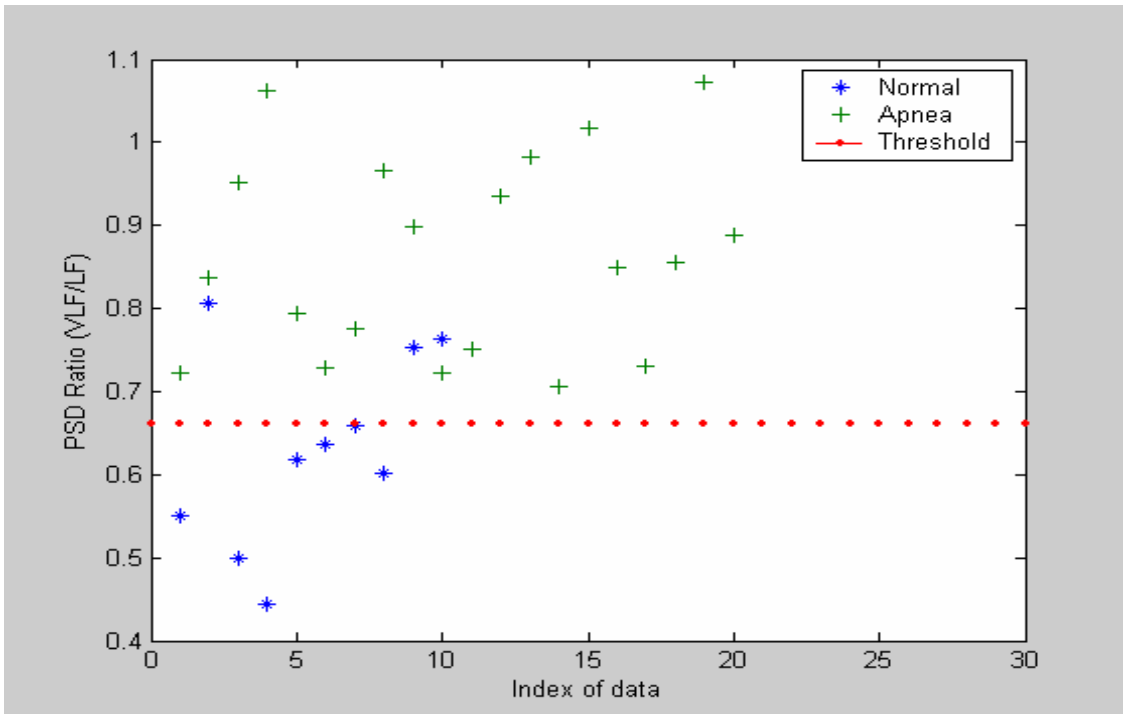


FIGURE 5: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using Wavelets

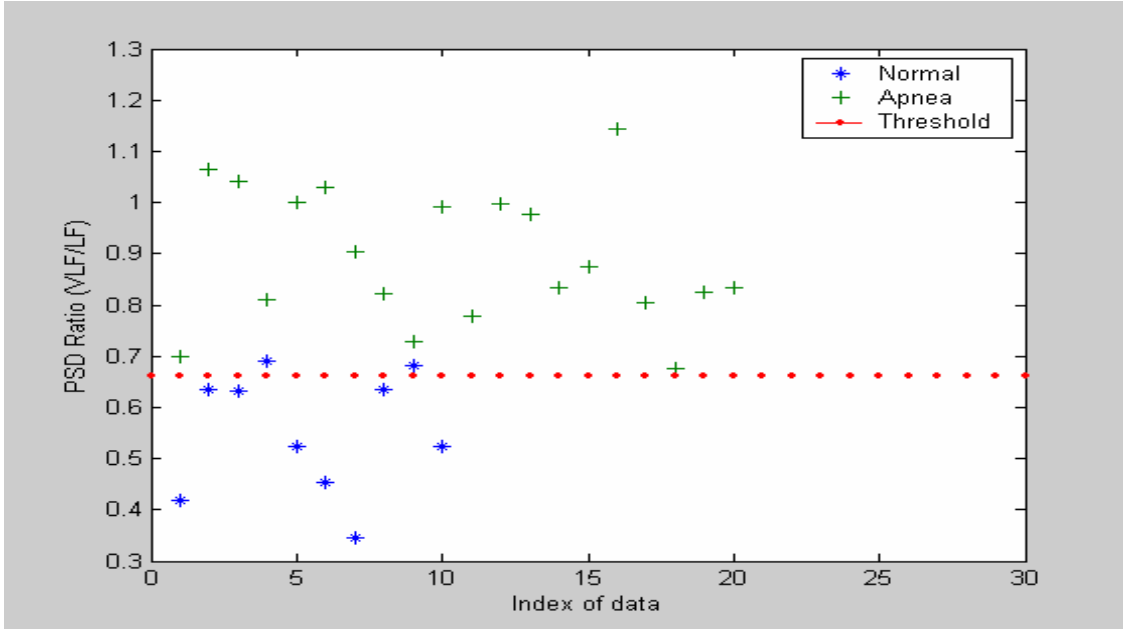


FIGURE 6: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Test Data using Wavelets

3.3 FFT Short Recording

To enhance the results of FFT spectral analysis the whole record length of RRI data is divided into short records. The FFT is implemented on each short record and PSD ratio of the VLF band to that of the LF band is computed for each short record. The PSD of the whole record is then computed by averaging the results of the short records. Results on MIT trial data and MIT test data are shown in Fig. 7 and Fig. 8 respectively for a short record of length 128. Table 5 shows the MIT-test results using different lengths of short records.

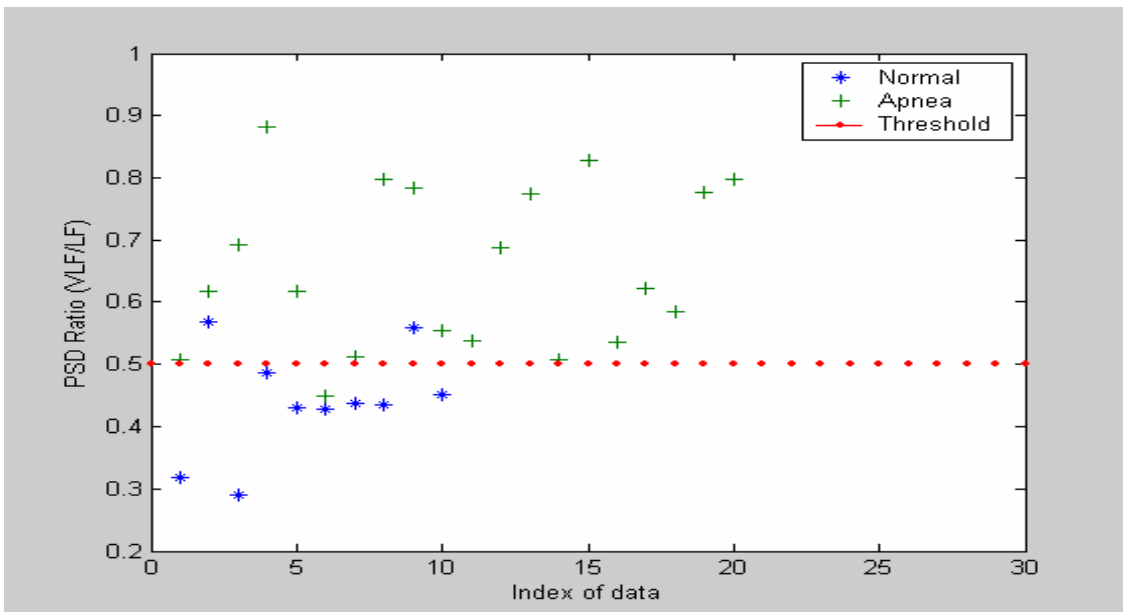


FIGURE 7: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using FFT Short Records

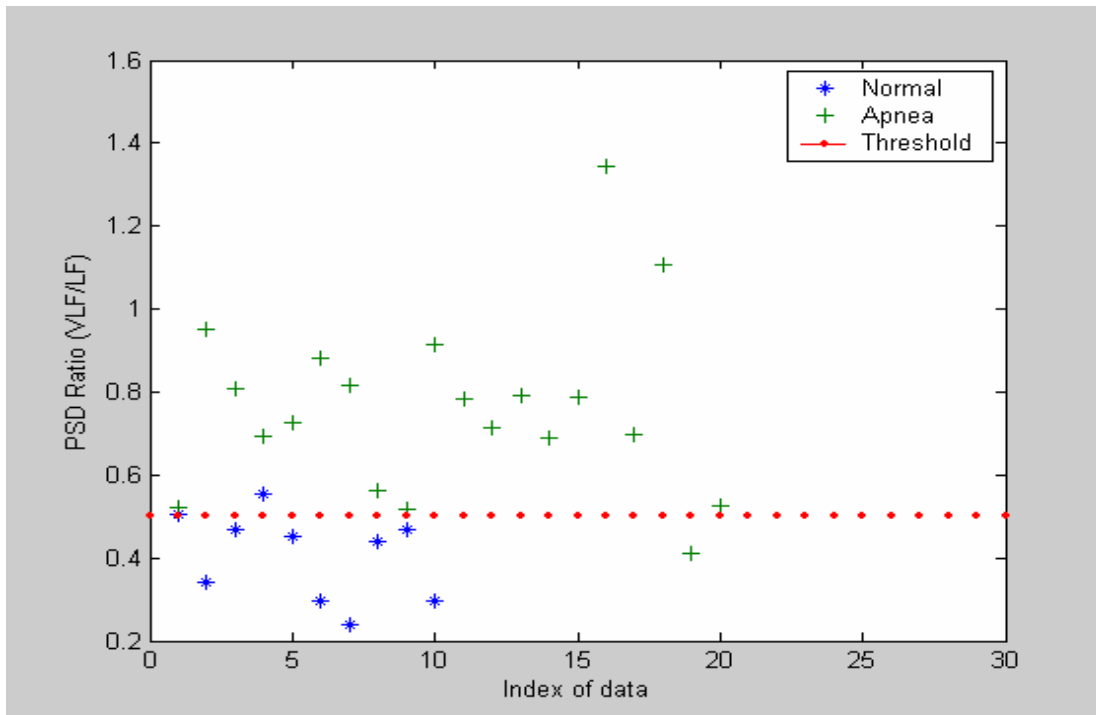


FIGURE 8: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Test Data using FFT Short Records

length of FFT	Specificity	Sensitivity	Accuracy
2048	6/10	19/20	25/30
1024	7/10	19/20	26/30
512	8/10	19/20	27/30
256	8/10	19/20	27/30
128	9/10	19/20	28/30

TABLE 5: Different Results of MIT-Test Data using FFT Short Records

3.4 FFT Short Recording with Zero-Padding

To increase the resolution of any spectral analysis an idea of zero-padding the signal to increase its length can be applied. We improve the results of our FFT spectral identification by adding zeros at the end of the short records to double its length and then the FFT algorithm is applied. The identification factor is found for each zero-padded short record and an average value is obtained then for the whole record. Fig. 9 and Fig. 10 show the results of MIT trail and MIT test data respectively by using a short record with 128 samples which is zero-padded with another 128 zeros. Table 6 lists the results of this improvement using different lengths.

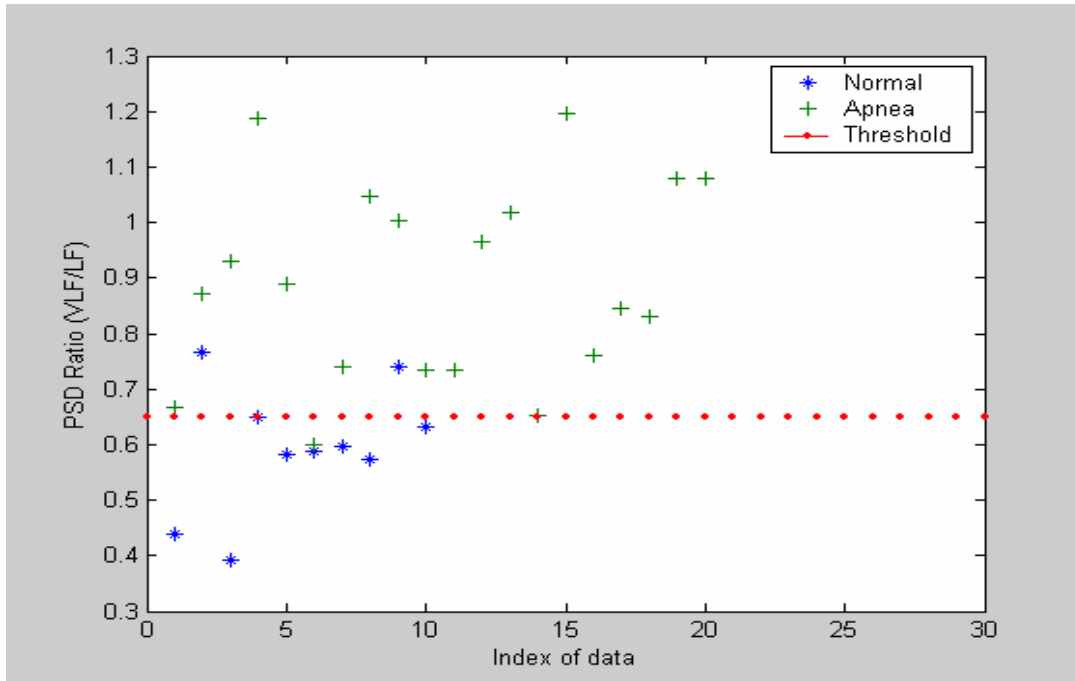


FIGURE 9: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Trial Data using FFT Short Records with Zero-Padding

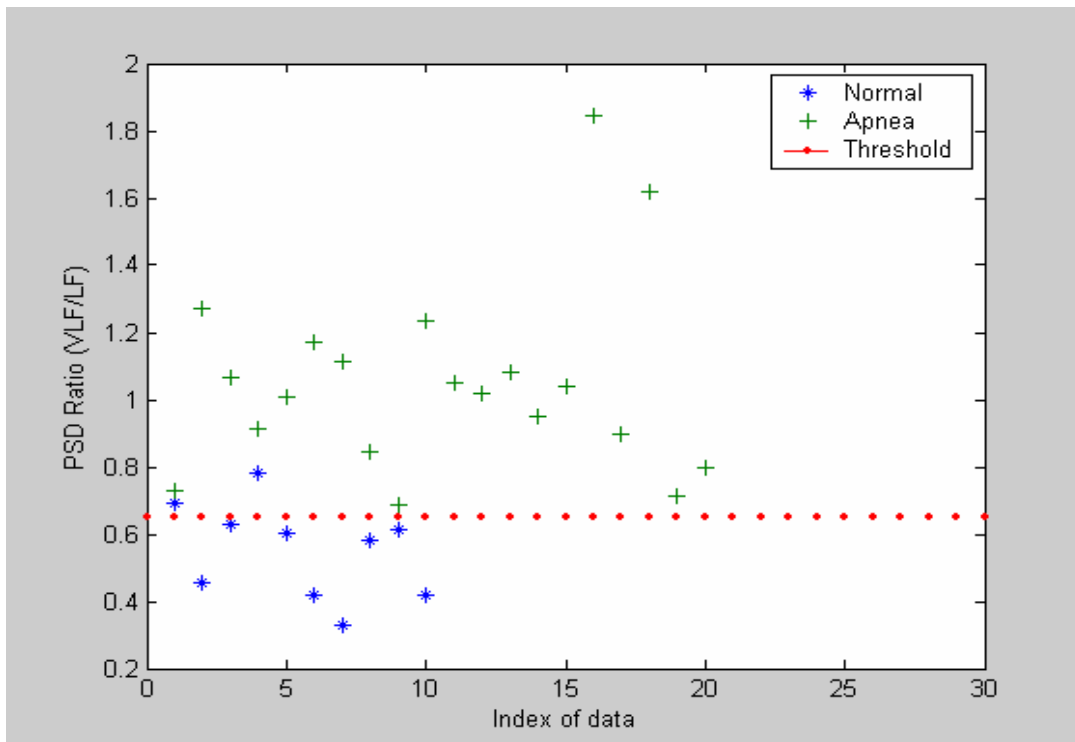


FIGURE 10: (VLF/LF) PSD Ratio of OSA and Normal Subject of MIT-Test Data using FFT Short Records with Zero-Padding

length of FFT+ Zeros Padded	Specificity	Sensitivity	Accuracy
1024 + 1024	6/10	20/20	26/30
512 + 512	8/10	19/20	27/30
256 + 256	8/10	20/20	28/30
128 + 128	8/10	20/20	28/30

TABLE 6: Different Results on MIT-Test Data using FFT Short Records with Zero-Padding

4. SUMMARY AND CONCLUSIONS

A summary of results of all methods used in this work are listed in Table 7 for better comparison.

Method	Specificity	Sensitivity	Accuracy
Wavelet	8/10	20/20	28/30 = 93%
FFT Long Recording	8/10	19/20	26/30 = 87%
FFT Short Recording	8/10	20/20	28/30 = 93%
FFT Short Recording + Zero Padding	8/10	20/20	28/30 = 93%

TABLE 7: Different results on MIT-Test Data using different techniques

The FFT has been implemented in this work as an identification tool in diagnosing of obstructive sleep apnea. The data used is a raw RRI data after simple preprocessing step. The original data has been taken from MIT databases. The FFT spectral analysis of the three main frequency bands (VLF, LF, and HF) and their ratios has been computed for the MIT trail data. The VLF/LF PSD ratio was found as a best identification factor. This identification factor has been tested then on MIT-test data and resulted in almost 87% identification accuracy. The improvement of the technique by using short records raises the identification accuracy up to 93%. The same improvement is obtained by zero-padding the short records and applying FFTs on double length records. The identification accuracy of FFT approaches that accuracy obtained using soft-decision wavelet approach.

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