INDIAN INSTITUTE OF TECHNOLOGY DELHI (IIT-D)

RESEARCH PROJECT REPORT ON

AUTOMATIC DETECTION OF OBSTRUCTIVE SLEEP APNEA USING HEART RATE VARIABILITY IN ECG SIGNALS

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ABSTRACT

Obstructive Sleep apnea (OSA) is a serious sleep disorder in which the obstruction of breathing occurs which may be dangerous in the normal living life. So the diagnosis of OSA in the electrocardiogram (ECG) is required in the research field of biomedical signal processing. So Heart rate variability is used for the diagnosis as this sleep disorder has a major effect on HRV. HRV involves the use of fast Fourier Transform (FFT) for the calculation of the low frequency and the high frequency power directly from the RR Intervals in the ECG signals. In this study we have implemented the HRV with the help of Wavelet Packet decomposition in which the evaluated RR Intervals are decomposed in the low frequency band (0.04-0.15 Hz) and the high frequency band (0.15-0.4 Hz). Then further the FFT will be used to calculate the power spectral densities in these frequency band and the Low frequency to high frequency ratios will be evaluated which will be the deciding factor for the detection of sleep apnea in the ECG signals. As the LF/HF ratio will be higher in the case of apnea ECG signal and it will be lower in the case of normal ECG signal. Both these methods are compared in this study on the basis of the LF power, HF power, LF/HF power for the detection of sleep apnea. These values will vary on the severity of the sleep apnea known as apnea–hypopnea index (AHI) which the number of apnea and hypopnea events per hour of sleep.

INTRODUCTION

Sleep Apnea is the sleep disorder in which the breathing is obstructed for few seconds or even few minutes as well. Sleep apneas can be classified as follows: obstructive (OSA), central (CSA), and a combination of the two called mixed (MSA). Among these the most common one is OSA whose symptoms include restless sleep, insomnia, trouble concentrating, mood changes, increased blood pressure and loud snoring. Approximately 6% of adults and 2% of children are affected by OSA. Males are affected almost twice than the number of women. There is no age constraint for sleep apnea but mostly 55 to 60 years old people are affected. About less than than 1% of people are affected by CSA. It can be detected in an electrocardiogram (ECG) during sleep stages.

The physiological phenomenon of variation in the time interval between heartbeats is known as Heart Rate variability (HRV), also known as RR variability which tells about the changes in the RR Interval (the interval between the successive R to R peak of QRS complex in an ECG signal). It is measured by the changes in the beat-to-beat interval of ECG signal. HRV Analysis can be done in the time domain as well as frequency domain. In time domain methods the features like: SDNN, the standard deviation of RR intervals, RMSSD ("root mean square of successive differences"), SDSD ("standard deviation of successive differences") and many more are extracted for detection of apnea. The classification can be done by the Support vector machines(SVM) and K-Means Clustering. Frequency domain methods assign bands of frequency and then number of RR intervals are estimated that match each band. The frequency bands are: high frequency (HF) from 0.15 to 0.4 Hz, low frequency (LF) from 0.04 to 0.15 Hz, and the very low frequency (VLF) from 0.0033 to 0.04 Hz. The importance of HRV analysis is that the low frequency powers and the high frequency power can be determined which can be effective in the detection of sleep apnea. Patients who suffer from OSA are having high levels of sympathetic nervous system activity as compared to the normal patients. So this sympathetic and parasympathetic activity need to be determined from the ECG data for the classification of sleep apnea. For this the low and the high frequency powers need be evaluated for the further calculation of the LF/HF ratio which will distinguish between the sleep apnea and the normal ECG as the LF power correspond to the sympathetic and parasympathetic activity in the ECG signal.

MATERIALS AND METHODOLOGY

Datasets

The sleep Apnea database was downloaded in the form of edf files as well as mat files from the website www.physionet.org. In this study twenty minutes (1200 seconds) of ECG Data was taken for the further processing. These ECG data has the sampling frequency of 100Hz. One category is of Normal ECG data and the other category is Apnea ECG data. The duration of the data can be varied as per requirement. Figure 1 shows the PQRSTU wave in the ECG signal.

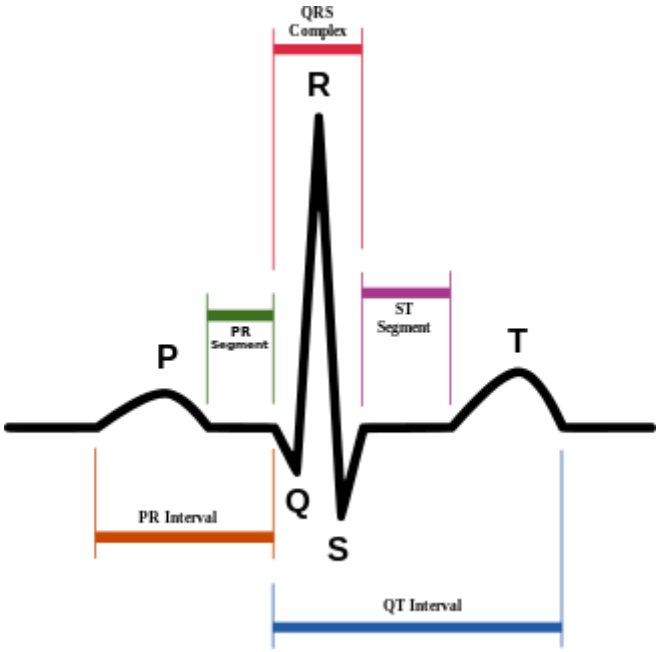

Figure 1. PQRSTU wave in the ECG signal.

RR Interval Estimation

An ECG signal consists of the P wave, QRS complex , T wave and a small U wave .The ECG signals are detrended if there are any trends in the signals and are denoised as well. Initially, all the R peaks are detected in the QRS complexes using Pan-Tompkins Algorithm or Thresholding algorithms. Once the R peaks are detected in an ECG signal, the times at which these peaks are detected are calculated and the consecutive differences between these R peak times are calculated known as RR Interval. In Pan Tompkins Algorithm, Cancellation of DC drift and normalization is done, then Low pass filtering and high pass filtering is applied accordingly. Derivative filtering is applied and squaring of the resultant output. Moving Window Integration is done in the end to get the Q R S points. Once these points are detected and marked in the signal, the R peaks can be calculated by the Thresholding technique in which the Thresholds are calculated for every segment of the signal and if the value of the signal is greater than that Threshold value, the R peaks are detected. The values of these R peaks are calculated accordingly. But the main concern regarding HRV is the RR Interval which the difference between the consecutive Times ($r(i)$ and $r(i+1)$) at which the R peaks are detected. In this way, the RR intervals

of the whole ECG data can be estimated using equation (1) and can be used for further processing in the frequency domain. The RR intervals are plotted with respected to time. The variations in the RR Intervals correspond to the HRV.

$$RR\,(i) = r(i+1) - r(i), \qquad i = 1,2,\ldots, n-1. \quad (1)$$

The LF/HF Ratio can be calculated by two methods. In the first method directly by the Power Spectral densities of the HRV in the Low frequency band and the high frequency band and then by dividing them, the ratio can be calculated. The second one which is more effective using the Wavelets Packets Decomposition. In this method initially the RR Intervals are reconstructed in the low frequency region and the high frequency region. The reconstruction of these RR Intervals is done by decomposing the RR Intervals via wavelet Packet tree to get the desired regions of Low frequency band (0.04-0.15 Hz) and high frequency band (0.15-0.4 Hz). Then the power of the Low frequency reconstructed RR intervals and of the high frequency reconstructed RR intervals are calculated via Fourier Transform method, then the ratio of these powers gives the LF/HF Ratio of HRV which helps in the detection of the Sleep Apnea. In the whole ECG signal wherever the sleep apnea is occurring the LF/HF ratio was getting increased according to the segments where there is no sleep apnea (normal ECG signal).

The next step in our procedure after data selection is data partitioning. In our work, three cases of partitioning were analyzed, as follows:

• Case 1. The apnea and regular data are partitioned into 10 second pieces
• Case 2. The apnea and regular data are partitioned into 15 second pieces
• Case 3. The apnea and regular data are partitioned into epochs of 30 second pieces.
Since apnea is defined as a pause in breathing, and can last from a few seconds to minutes (almost >=10 sec); we investigate the three above cases to determine the best accuracy that can be achieved.

Features Extraction

Our technique relies on an effective combination of ECG signal features which is a novel hybrid of features extracted. According to Heart rate variability, the following time domain ECG features which are most effective for apnea detection are calculated:

• Mean epoch and recording RR-interval.
• Standard deviation of the epoch and recording RRinterval.
• The NN50 measure (variant 1), defined as the number of pairs of adjacent RR- intervals where the first RR interval exceeds the second RR- interval by more than 50 ms.
• The NN50 measure (variant 2), defined as the number of pairs of adjacent RR-intervals where the second RR-interval exceeds the first RR interval by more than 50 ms.
• Two pNN50 measures, defined as each NN50 measure divided by the total number of RR-intervals.
• The SDSD measures, defined as the standard deviation of the differences between adjacent RR intervals.
• The RMSSD measures, defined as the square root of the mean of the sum of the squares of differences between adjacent RR- intervals.
• Median of RR-intervals.
Inter-quartile range, defined as difference between 75th and 25th percentiles of the RR-interval value distribution.
• Mean absolute deviation values, defined as mean of absolute values obtained by the subtraction of the mean RR-interval values from all the RR-interval values in an epoch.

After the extraction of these time domain features, we need some classification algorithms to train and classify the apneic and non apneic ECG signals. In this study we have used the 2 machine Learning algorithms one is Support vector machines (supervised learning) and the other is K-Means clustering

(unsupervised learning). So these epochs are trained and then classified using these two algorithms for better accuracy. The block diagram of the overall methodology used in this study is shown in Figure2.

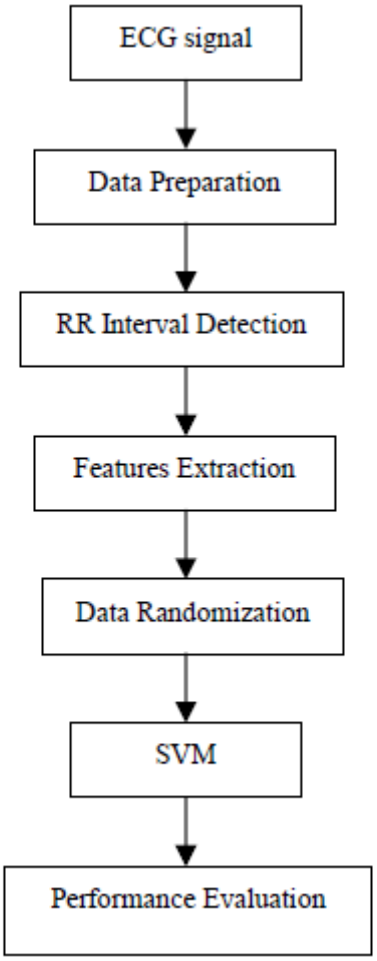

Figure 2. Schematic diagram of the system.

Support Vector Machines

We use Support Vector Machines (SVMs) as a classification (also known as supervised learning) method in order to investigate apneaic epoch detection. SVMs are learning methods, which aim to find the optimal separating plane that analyze data and recognize pattern used for regression analysis. In SVM, P data is classified to which class it belongs, by points with a $(P - 1)$ dimensional hyperplane, which is called a linear classifier. The optimal hyperplane that separates the clusters of vectors is found by SVM modeling. The cases with one category of the target variable are on one side of the plane and cases with the other category are on the other side of the plane. Figure 3 illustrates the working principle of SVM.

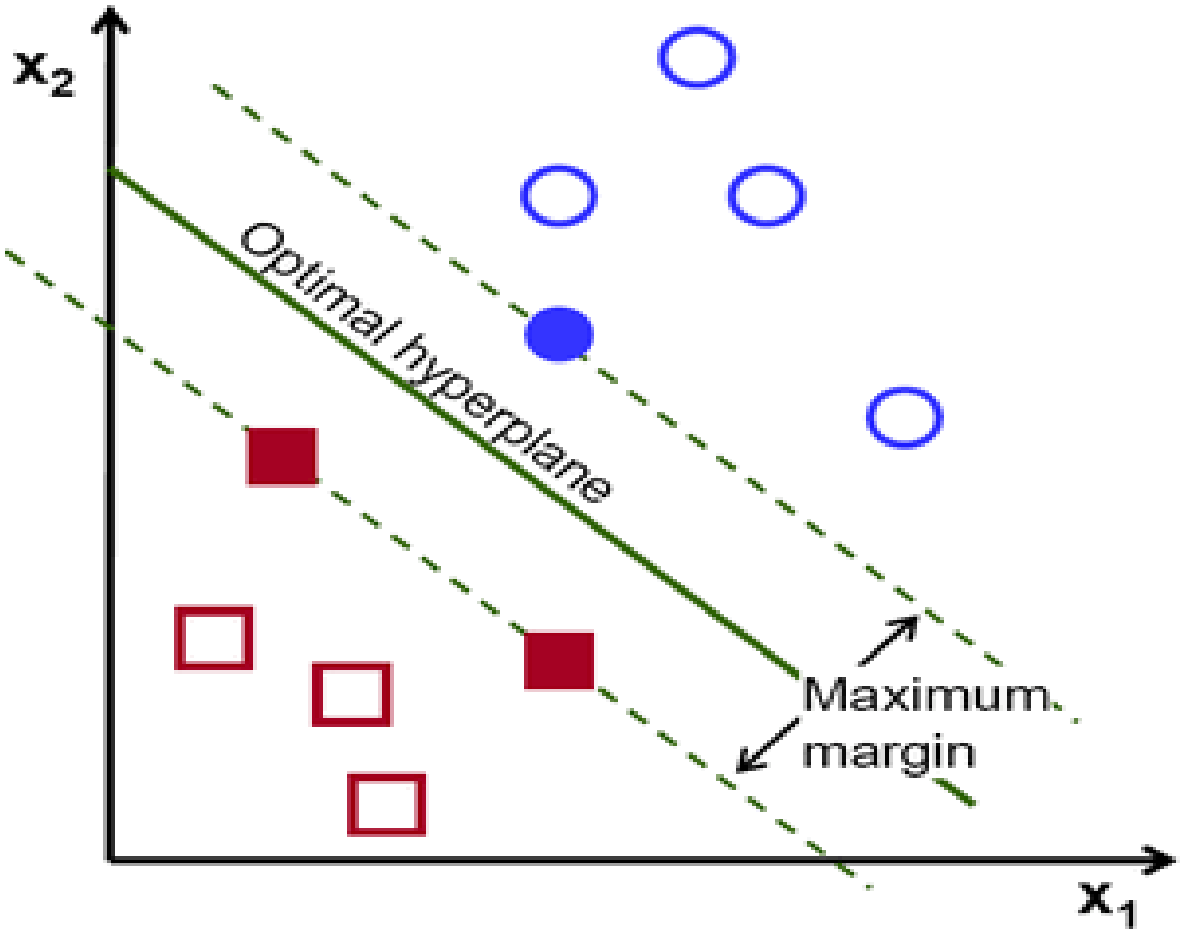

Figure 3. The working principle of SVM.

A good separation between the two possible classes is achieved by building a maximal margin hyperplane. The margin maximizes the distance between the classes and the nearest data point of each class. In general, the larger the margin is, the lower the generalization error of the classifier. Figure 4 shows the trade off margin choice. In addition, SVMs handles the separation by a kernel function to map the data into a different space with a hyperplane. SVM gives the flexibility for the choice of the kernel, as shown in Figure 5 Linear, polynomial and radial can be taken as an example for a kernel function.

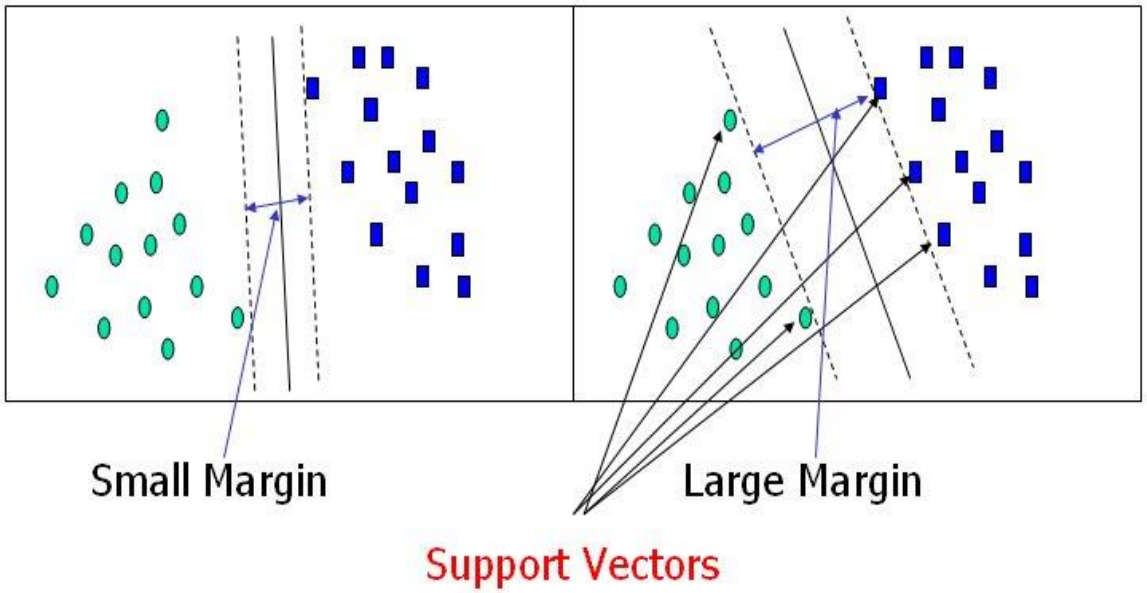

Figure 4. The trade off margin choice

The choice of a kernel depends on the problem we are trying to model. Polynomial kernels are well suited for problems where all the training data is normalized, and it allows to model feature conjunctions up to the order of the polynomial. Radial basis functions allow picking out circles (or hyperplanes). In contrast, the linear kernel, allows only picking out lines (or hyperplanes).In our implementation, we use a linear kernel function to map the training data into kernel space. In the optimization process, we use a method called sequential minimal optimization to find the separating hyperplane.

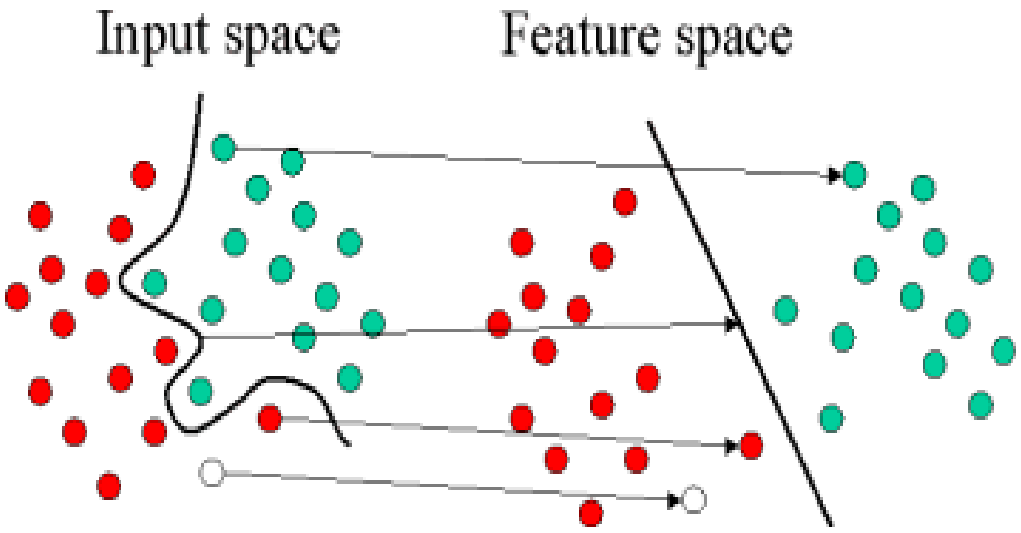

Figure 5. Choice of Kernel function

SVM: Mathematics behind it!

- Separating hyper-plane

$$w_1x_1 + w_2x_2 + w_0 = 0$$

- Any point lying above the SH satisfies

$$w_1x_1 + w_2x_2 + w_0 > 0$$

- Any point lying below the SH satisfies

$$w_1x_1 + w_2x_2 + w_0 < 0$$

- Adjusting the weights

$$H_1 : w_1x_1 + w_2x_2 + w_0 \geq 1 \, for \, y_i = +1$$

$$H_2 : w_1x_1 + w_2x_2 + w_0 \leq -1 \, for \, y_i = -1$$

- Combining, we get

$$y_i(w_1x_1 + w_2x_2 + w_0) \leq 1 \forall i$$

- Any training tuple that falls on H1 or H2 satisfies above inequality is called Support Vectors (SVs)
- SVs are most difficult tuples to classify & give most important information regarding classification

K-Means Clustering

K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The results of the *K*-means clustering algorithm are:

1. The centroids of the *K* clusters, which can be used to label new data

2. Labels for the training data (each data point is assigned to a single cluster)

Figure 6 represents the formation of Clusters in K-Means Clustering

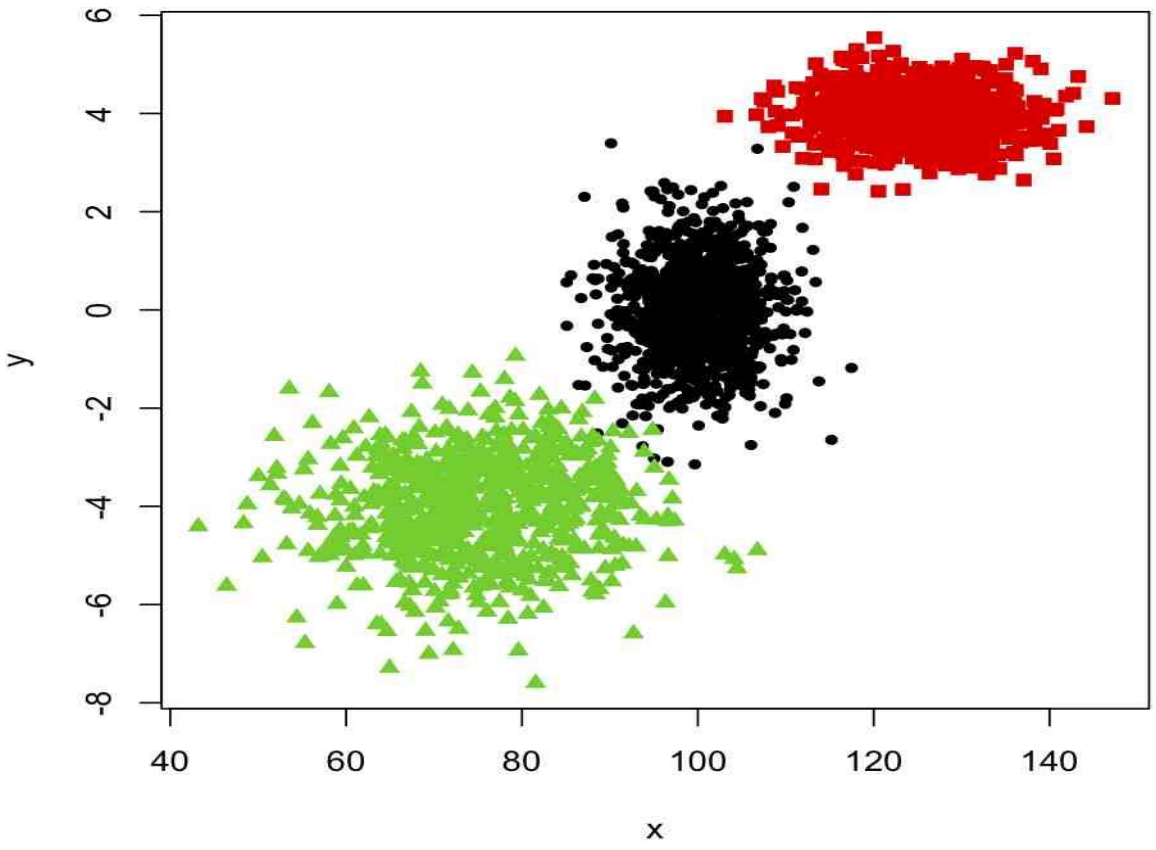

Figure 6. Formation of Clusters in K-Means Clustering

Rather than defining groups before looking at the data, clustering allows you to find and analyze the groups that have formed organically. The "Choosing K" section below describes how the number of groups can be determined.

Each centroid of a cluster is a collection of feature values which define the resulting groups. Examining the centroid feature weights can be used to qualitatively interpret what kind of group each cluster represents.

The K-means clustering algorithm uses iterative refinement to produce a final result. The algorithm inputs are the number of clusters K and the data set. The data set is a collection of features for each data point. The algorithms starts with initial estimates for the K centroids, which can either be randomly generated or randomly selected from the data set. The algorithm then iterates between two steps:

1. Data assigment step:
Each centroid defines one of the clusters. In this step, each data point is assigned to its nearest centroid, based on the squared Euclidean distance. More formally, if ci is the collection of centroids in set C, then each data point x is assigned to a cluster based on

where dist(·) is the standard (L2) Euclidean distance. Let the set of data point assignments for each ith cluster centroid be Si.

2. Centroid update step:
In this step, the centroids are recomputed. This is done by taking the mean of all data points assigned to that centroid's cluster. Figure 7 represents Iterations for Centroid estimation in K-Means Clustering

The algorithm iterates between steps one and two until a stopping criteria is met (i.e., no data points change clusters, the sum of the distances is minimized, or some maximum number of iterations is reached).
This algorithm is guaranteed to converge to a result. The result may be a local optimum (i.e. not necessarily the best possible outcome), meaning that assessing more than one run of the algorithm with randomized starting centroids may give a better outcome.

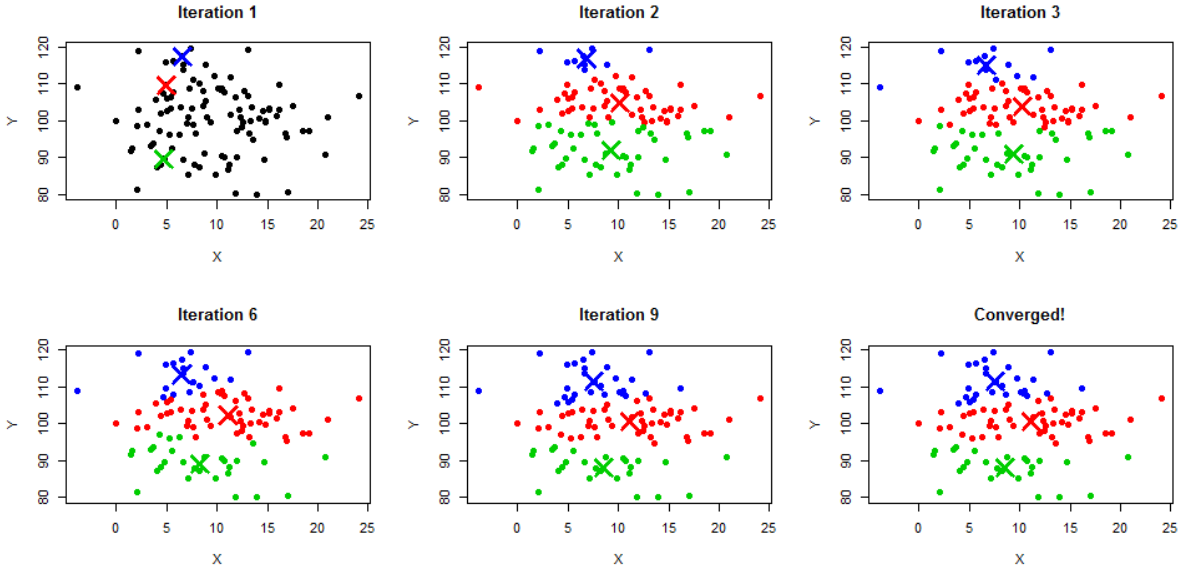

Figure 7. Iterations for Centroid estimation in K-Means Clustering

Choosing K

The algorithm described above finds the clusters and data set labels for a particular pre-chosen K. To find the number of clusters in the data, the user needs to run the K-means clustering algorithm for a range of K values and compare the results. In general, there is no method for determining exact value of K, but an accurate estimate can be obtained using the following techniques.

One of the metrics that is commonly used to compare results across different values of K is the mean distance between data points and their cluster centroid. Since increasing the number of clusters will always reduce the distance to data points, increasing K will always decrease this metric, to the extreme of reaching zero when K is the same as the number of data points. Thus, this metric cannot be used as the sole target. Instead, mean distance to the centroid as a function of K is plotted and the "elbow point," where the rate of decrease sharply shifts, can be used to roughly determine K.

A number of other techniques exist for validating K, including cross-validation, information criteria, the information theoretic jump method, the silhouette method, and the G-means algorithm. In addition, monitoring the distribution of data points across groups provides insight into how the algorithm is splitting the data for each K.

Evaluation of LF/HF Ratio

Then the Power spectral densities of the RR intervals are evaluated by taking the fourier Transform of the RR Intervals and the squaring. Because the signal is real-valued, only need power estimates for the positive or negative frequencies are required. For the conservation of the total power, multiply all frequencies that occur in both sets -- the positive and negative frequencies - by a factor of 2. Zero frequency (DC) and the Nyquist frequency do not occur twice. Finally the periodogram in decibels per hertz using FFT can be obtained. These are the powers of the Heart rate variability which includes all the frequency band. But for the estimation of Low frequency to High frequency Ratio (LF/HF Ratio) only the powers which fall under the Low frequency range (0.04-0.15 Hz) and the high frequency range (0.15-0.4 Hz) are considered. The Low and the high powers can be calculated by integrating over these frequency range. Then the LF/HF Ratio can be calculated by dividing these two powers. This LF/HF ratio is very essential for the Obstructive sleep Apnea detection in the ECG signals.

LF/HF Ratio using Wavelets Packet Decomposition Method

A wavelet is a wave-like oscillation in which the amplitude begins at zero, increases, and then decreases back to zero. There are many types of wavelets available for example: symlets, haar, Daubechies, coiflets wavelets, etc. The types of wavelets are selected according to the input signals. Wavelets are very useful for the denoising in the signal processing. A large number of wavelet transforms are available for different applications in the signal processing like: Continuous wavelet transform (CWT), Discrete wavelet transform (DWT), Wavelet packet decomposition (WPD). In this case Wavelets Packets decomposition will be used for decomposing the RR Intervals (HRV) into frequency sub-bands. It is also known as Optimal Subband Tree Structuring (SB-TS) (sometimes known as just Wavelet Packets or Subband Tree) is a wavelet transform in which discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform (DWT).

In the DWT, Only The previous wavelet approximation coefficients (cA_j) are passed through discrete-time low and high pass quadrature mirror filters for each level for calculation. While in WPD, both the detail (cD_j (in the 1-D case), cH_j, cV_j, cD_j (in the 2-D case)) and approximation coefficients are decomposed to create the full binary tree, also known as wavelet packet tree.If we Subsample a signal sampling rate is reduced, or some of the samples of the signal are removed..

The figure 8 shows the Wavelet Packet decomposition over 3 levels where g[n] is the low-pass approximation coefficients and h[n] is the high-pass detail coefficients.

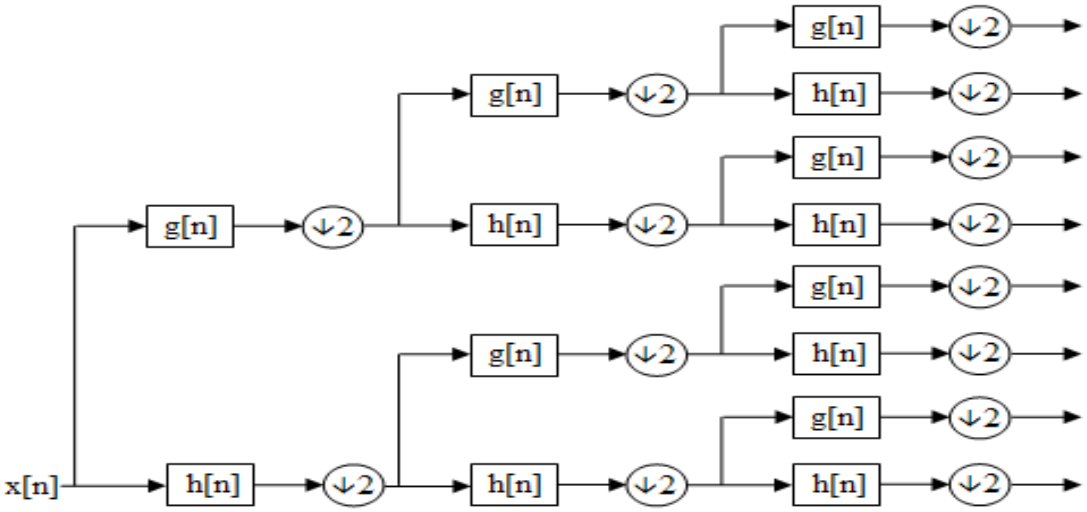

Figure 8. Wavelet Packet decomposition upto 3 levels

In general if n levels of decomposition takes place, the WPD produces 2n different sets of coefficients (or nodes) while (3n + 1) sets for the DWT. However, the overall number of coefficients is still the same and there is no redundancy because of the downsampling process.

After the Wavelet packet decomposition, the wavelet packet tree is constructed according to the sampling frequency of the RR Intervals. The tree is decomposed till the desired frequency bands are acquired and then the required Coefficients of certain levels in the packet tree are reconstructed accordingly to get the Low frequency reconstructed and the high frequency reconstructed RR Intervals. After having these signals, the Powers can be calculated using FFT. The Low frequency band power and the Low frequency band power are evaluated respectively and the ratio of these two powers gives the LF/HF Ratio which is used for the sleep Apnea detection in an ECG signal.

RESULTS

Initially R peaks are detected from the ECG data and then the RR Intervals are calculated from those R peaks as shown in the figure 9. After RR Intervals evaluation, the RR interval plot in figure 10 with respect to time shows that in 1200 sec of this apnea ECG data 1214 RR intervals are determined so the sampling frequency of RR Intervals of this apnea data is 1.01Hz (1214/1200). Like this the sampling frequency of RR intervals in every ECG signal can be evaluated and in our case it is around 1 Hz. The Power spectral Density of the RR Intervals is plotted by the FFT. Then after taking the area under the curves in the low frequency band (0.04-0.15 Hz) and the high frequency band (0.15-0.4 Hz). The Low frequency and the high frequency components are evaluated through which the LF/HF Ratio is calculated for every ECG data. The Low frequency power, high frequency power and LF/HF Ratio is shown in the table for different apnea ECG data and normal ECG data which differentiates between the sleep Apnea and normal ECG data on the basis of LF/HF Ratio value.

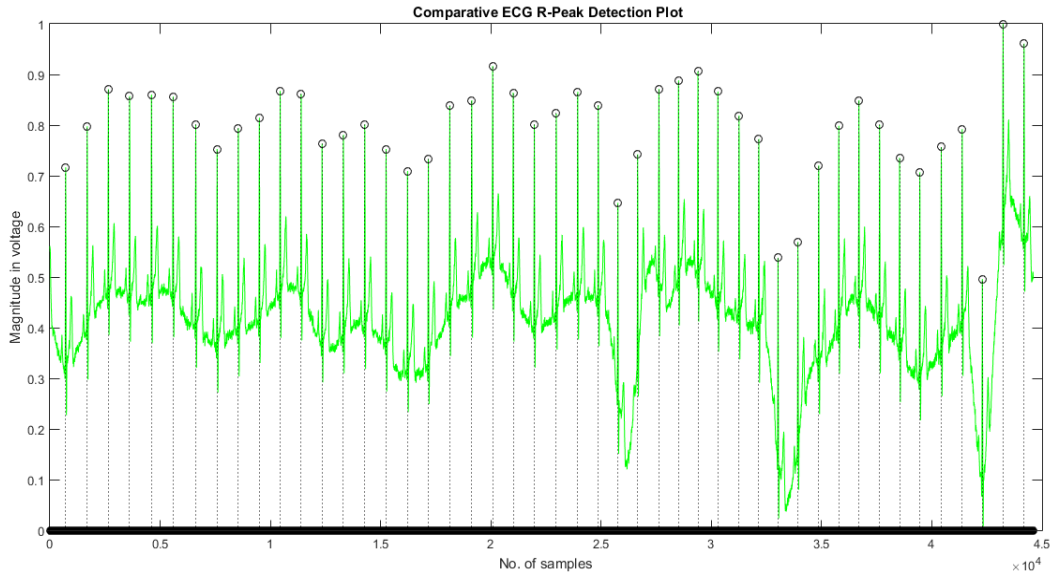

Figure 9. R peak detection plot

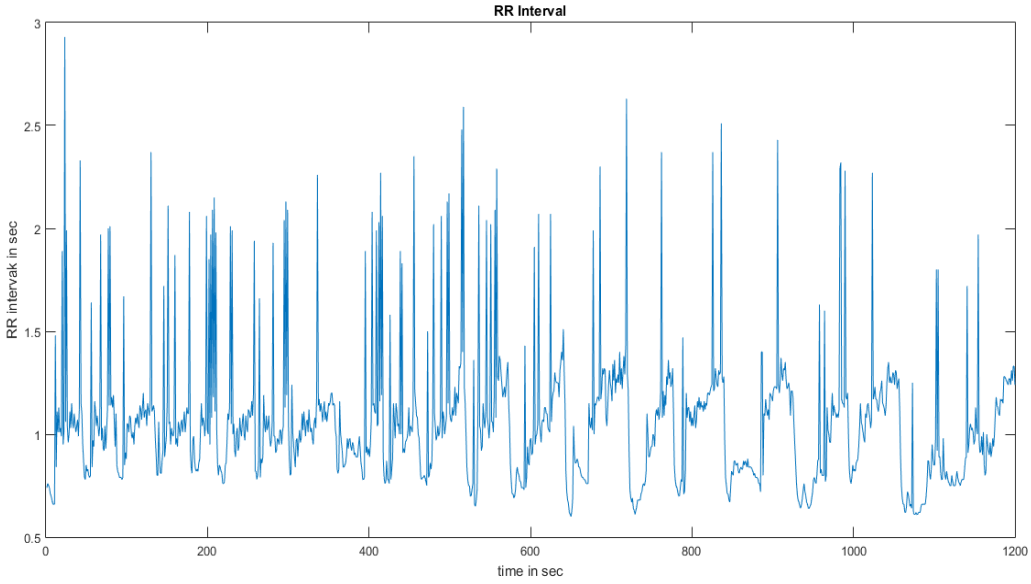

Figure 10. RR Interval Plot in seconds with respect to time

Figure 11 and 12 shows the FFT and PSD of evaluated RR Intervals respectively.

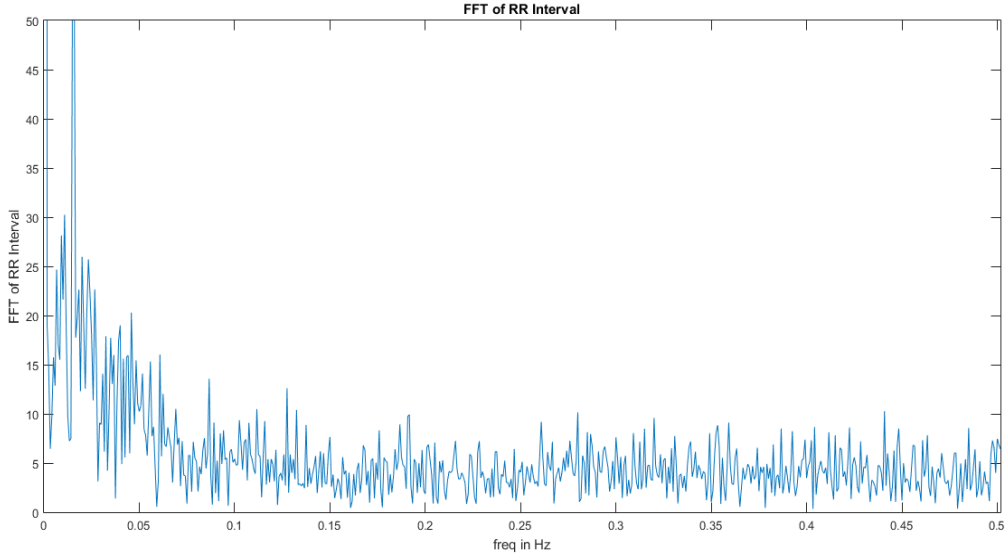

Figure 11. Fast Fourier Transform of RR Interval Plot with respect to frequency

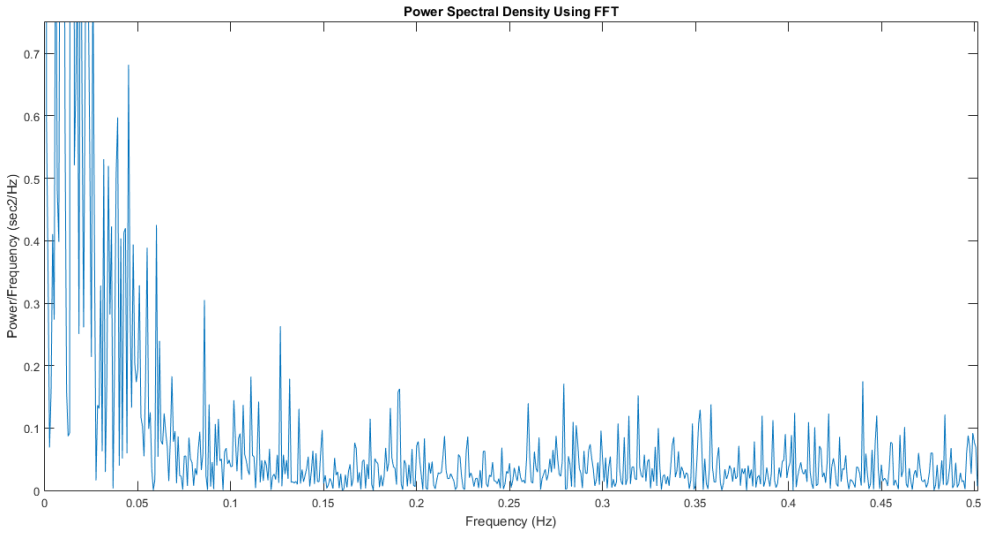

Figure 12. power spectral density of RR Interval Plot with respect to frequency

So the LF, HF power and LH/HF ratios can be evaluated in both cases Apnea and normal ECG signals. Table 1 and 2 shows LF, HF Power and LF/HF Ratio of Apnea and Normal EDF files

Apnea EDF Files	LF Power(in sec^2)	HF Power(in sec^2)	LF/HF Ratio
A1	0.0095	0.0086	1.0976
A6	0.0034	0.0029	1.1985
A7	0.0023	0.0008	2.5947
A14	0.0082	0.0046	1.7678
A21	0.0299	0.0163	1.8337

Table 1. LF, HF Power and LF/HF Ratio of Apnea EDF files

Normal EDF Files	LF Power(in sec^2)	HF Power(in sec^2)	LF/HF Ratio
N1	0.0165	0.0434	0.3806
N2	0.0027	0.0061	0.4448
N4	0.0103	0.0272	0.3803
N7	0.0640	0.1386	0.4621
N8	0.1051	0.2347	0.4480

Table 2. LF, HF Power and LF/HF Ratio of Normal EDF files

LF/HF Ratio from Wavelets Packet Decomposition

The other method of calculating the LF/HF ratio which is a WPD illustrates the better analysis of the HRV in the frequency domain. As the sampling frequency (fs) is 1 Hz so the Wavelet Packet Decomposition is going to occur from 0.5Hz (fs/2), as the maximum frequency in a signal of sampling frequency fs is fs/2. So in the wavelet packet tree the decomposition starts from 0.5 Hz till the 5^{th} level as per the requirement of the low frequency and high frequency band. At first level 0-0.25 Hz and 0.25-0.5 Hz and so on. The wavelet Packet tree is shown in the figure 13. Then for the reconstruction of the RR Intervals the 5^{th} level is going to be considered. For low frequency region the nodes number from 3 to 9 will be reconstructed by adding them and for high frequency region the nodes number from 10 to 25 will be reconstructed by adding them. So the low frequency and the high frequency reconstructed RR intervals are shown in the figure 14 and figure 15 respectively.

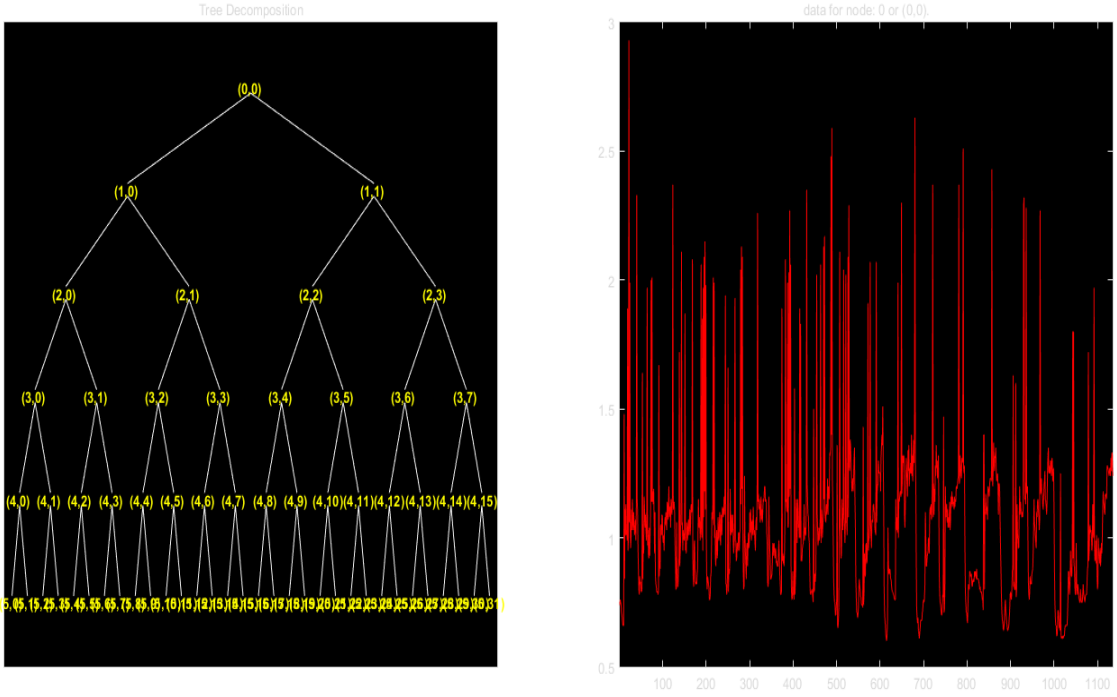

Figure 13. Wavelet Packet decomposition Tree upto 5 levels

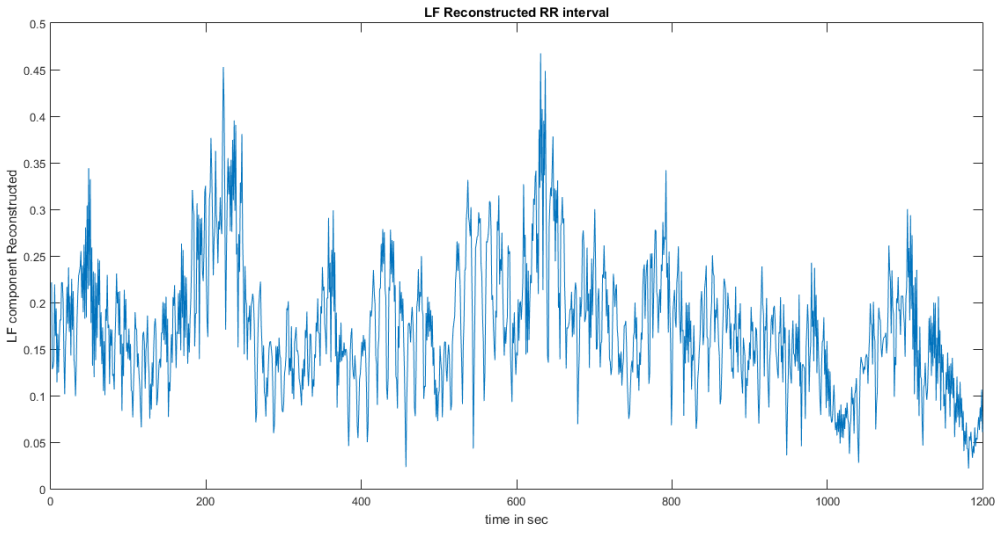

Figure 14. Low frequency reconstructed RR Interval Plot in seconds with respect to time

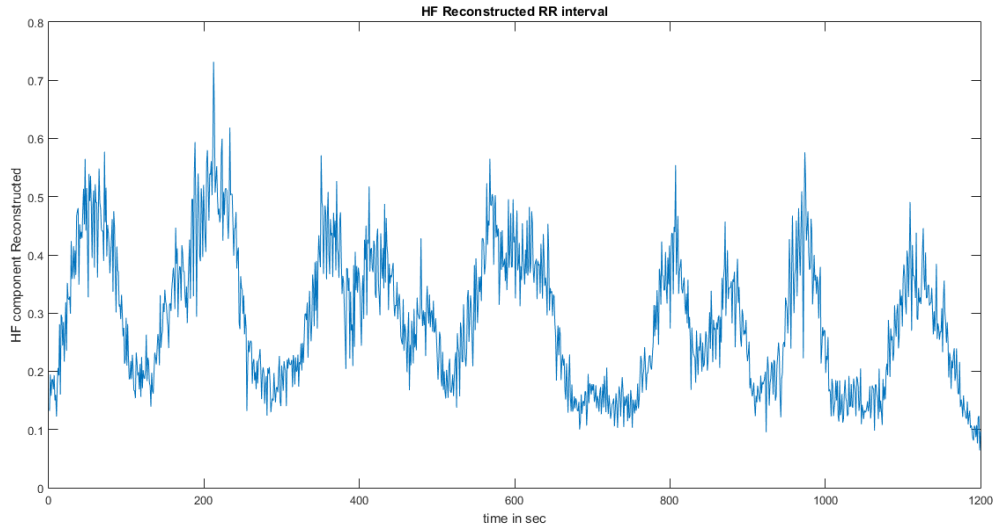

Figure 15. High frequency reconstructed RR Interval Plot in seconds with respect to time

Once these RR Intervals are reconstructed in the desired frequency bands (LF and HF band), the low frequency power and the high frequency powers are evaluated from the Fourier transform of these reconstructed LF and HF RR intervals. The Power spectral density of both these reconstructed signals are plotted as shown in the figure16 and figure 17. The area under the curves will give the respective LF power and HF power

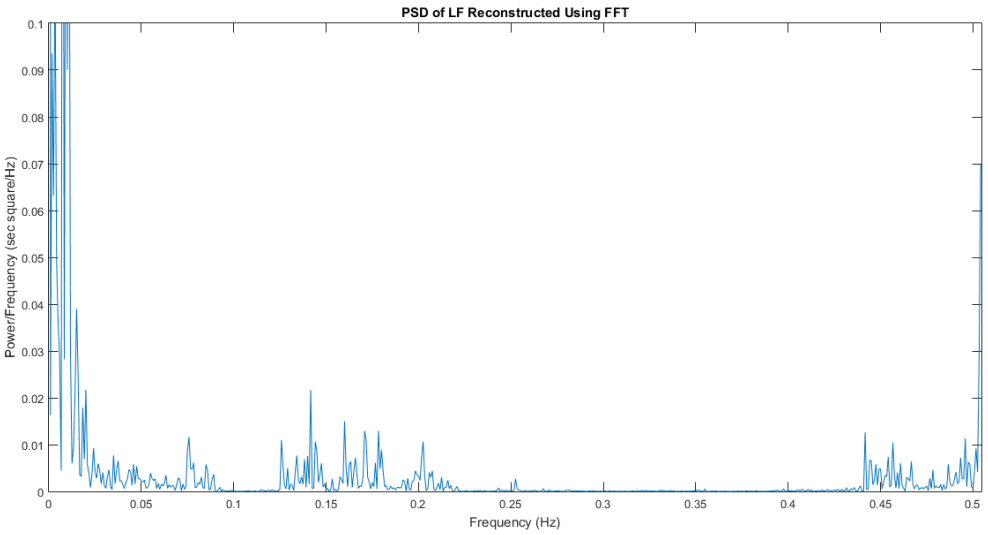

Figure 16. power spectral density of low frequency reconstructed RR Interval Plot

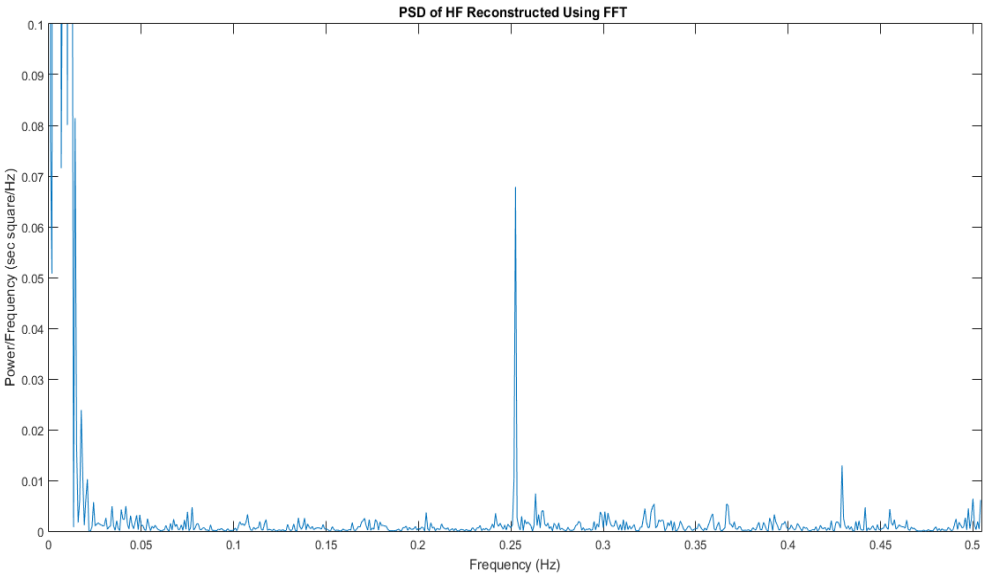

Figure 17. power spectral density of High frequency reconstructed RR Interval Plot

The ratio of these LF and HF powers will give the LF/HF ratio which will be analysed for sleep apnea detection. Table 3 and 4 shows the LF, HF Power and LF/HF Ratios for Apnea and Normal EDF files

Apnea EDF Files	LF Power(in sec^2)	HF Power(in sec^2)	LF/HF Ratio
A1	0.0346	0.0658	0.526
A6	0.0146	0.0270	0.545
A7	0.007	0.0068	1.0401
A14	0.0215	0.0381	0.564

Table 3. LF, HF Power and LF/HF Ratio of Apnea EDF files

Normal EDF Files	LF Power(in sec^2)	HF Power(in sec^2)	LF/HF Ratio
N1	0.1087	0.4349	0.2499
N2	0.0162	0.0672	0.2384
N4	0.0217	0.0922	0.2355
N7	0.0632	0.2961	0.2239
N8	0.3598	1.4327	0.2511

Table 4. LF, HF Power and LF/HF Ratio of Normal EDF files

Performance Evaluation

Once the time-domain Features were extracted and then trained using SVM and K-Means Clustering and then can be predicted and tested on the different datasets. We evaluated the effectiveness of our model on the Apnea- ECG database, using different records available in that database. The model was implemented using MATLAB toolset. To evaluate the performance of the classification system, two statistical indicators, Sensitivity (Se) and Specificity (Sp) in addition to the Accuracy (Acc) have been used. The sensitivity of a test is the percentage of patients in the OSA positive group correctly diagnosed, whereas the specificity is the percentage of subjects in the OSA negative group correctly classified by the test. Table I, II and III show the classification results for the three cases mentioned in the data partitioning step. Our model was based on a linear kernel SVM using various RR-interval features of the ECG signal. The three cases used here are: (i) 10 seconds data partitioning, (ii) 15 seconds, and (iii) 30 seconds. The accuracy of our approach is 86.1%, 96.5%, and 95%, respectively.

From Table II, SVM with linear kernel using 15 second epochs shows the best classification accuracy with high successful rate of correct prediction. Figure 18. Shows the Accuracy analysis of Apnea detection for different segments.

TABLE I
10 sec. (Accuracy is 86.1%)

Input\Output	*Regular*	*Apnea*
Regular	**97.2%**	2.78%
Apnea	25%	**75%**

TABLE II
15 sec. (Accuracy is 96.5%)

Input\Output	*Regular*	*Apnea*
Regular	**100%**	0%
Apnea	7.1%	**92.9%**

TABLE III
30 sec. (Accuracy is 95%)

Input\Output	*Regular*	*Apnea*
Regular	**100%**	0%
Apnea	10%	**90%**

Figure 18. Accuracy analysis of Apnea detection for different segments

DISCUSSION

The LF/HF ratio in the ECG signal denotes the sympathovagal balance. Both these methods give almost the same LF/HF ratios with slight difference. The inference what we can get is that the LF power and the LF/HF Ratio is getting increased in sleep Apnea case as compared to the normal case which signifies that there is a strong sympathetic activity in the ECG signal. HRV may also be affected during daytime. By comparing these two methods in the first method the RR Intervals were directly considered for the LF/HF ratios calculation. The low frequency band power and the high frequency band power were decided directly from the fourier transform of RR interval without removing the frequencies out of the required range. Those unnecessary frequencies were just not considered in the area under the curves for the Low and the high frequency power calculations.

While in the case of Wavelet packet decomposition method, the RR intervals are denoised or they were reconstructed by removing those unnecessary frequency bands (0-0.04 Hz and 0.4-0.51Hz) and the RR intervals in the required range were calculated and reconstructed in the LF and HF band. The LF and HF powers were calculated from those reconstructed signals. There is no doubt that these powers and LF/HF ratio are going to vary from data to data. From these results it is clear that the LF/HF ratios are having dependency on the sleep stages and the ages of the patient. The table 5 below shows the values with and without using Wavelet packet decomposition.

Without WPD		**With WPD**	
LF Power	LF/HF ratio	LF Power	LF/HF ratio
0.0095	1.0976	0.0346	0.526
0.0034	1.1985	0.0146	0.545
0.0023	2.5947	0.007	1.0401
0.0082	1.7678	0.0215	0.564
0.0299	1.8337	0.0211	0.583

Table 5. LF Power and LF/HF Ratio of Apnea EDF files with and without WPD

CONCLUSION

This study done to diagnose the OSA in the ECG signal by performing the heart rate variability using frequency- domain analysis in patients with Obstructive Sleep Apnea (OSA) proves that there was increment in the sympathetic activity and a parasympathetic attenuation in patients with OSA and the LF power is higher and the HF power is lower so the LF/HF ratios are increased in the OSA patients as compared to the normal patients. These values are also going to have the dependency on the severity of apnea. Both these methods implemented here are verifying that the OSA has higher LF power and LF/HF ratio. Further the study can be extended to break the long ECG signals into segments of particular duration and by overlapping those segments of particular duration and this methodology can be applied for the calculation of LF/HF ratios of these segments and the data can be interpreted that in which duration the sleep apnea is detected in the entire ECG data.

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