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ECG signal recordings analysis for detection of sleep apnea

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Abstract: Sleep Apnea may be characterized as the sleep disorder occurs due to breaks or pauses in normal breathing process of an individual during sleep. There are various signals such as EEG signals, Polysomnographic signals, respiratory signals; ECG signals have been used for the identification of sleep apnea. This paper describes the implementation of our proposed automated algorithm for the detection of sleep apnea using ECG signal recordings with the help of wavelet transform. There are number of associated criticalities for which the ECG signal classification can be applied. One of such classification category includes sleep disorder identification known as sleep apnea. The statistical features have been extracted from the ECG signal for the classification purpose. The SVM classifier has been used for this purpose giving accuracy of 93.00% approx.

Keywords: Apnea, ECG, Sleep, SVM, Wavelet.

1. INTRODUCTION

Sleep is defined as naturally recapitulate resting state of an individual body. Polysomnography [PSG] is a tool which is used for the diagnosis of various sleep disorders [1].There are various sleep disorders which occur during sleep such as narcolepsy, insomnia, restless leg Syndrome and sleep apnea. Sleep Apnea is considered as the serious sleep syndrome. Sleep apnea is identified by the occurrence of pauses in breathing during sleep. These pauses are commonly known as the episodes of sleep apnea. Each episode of sleep apnea may lasts up to 10 seconds or more. Sleep Apnea may be characterized as Obstructive, Central and mixed sleep apnea [2].

Obstructive sleep apnea is caused by the physical blockage of airflow. Central sleep apnea is caused by the lack of respiratory efforts despite physical blockage whereas mixed sleep apnea is caused by the combined effect of both obstructive and central sleep apneas i.e in mixed sleep apnea, transition from central to obstructive apnea characteristics occur during the apnea events [3].

One of the most effective approaches to find the sleep apnea disorder is with the help of ECG signal analysis. This ECG signal analysis approach is very suitable to diagnosis the criticality of diseases. The characteristics exploration of ECG signals is done in sleep to identify the sleep distortion.

Fig. 1: Normal Airway and Closed Airway (Apnea) [2]

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1.1 Electrocardiograph (ECG)

Electrocardiography or ECG is the record of the activity of heart in electrical form. Conventionally this is in the form of a trans thoracic reading of the electrical activity of the heart over a period of time, as sensed by electrodes connected to the individual's body and recorded and displayed with the help of device peripheral to the body. The record produced by this non persistent method is termed an electrocardiogram. The ECG consists of PQRST waves [4].

P wave is the first wave which represents contraction and depolarization of the right and left atria. The QRS complex points out the time for the ventricles to Depolarize and give info about the conduction troubles in the Ventricles such as bundle branch block. T wave indicates the ventricular repolarization [5].

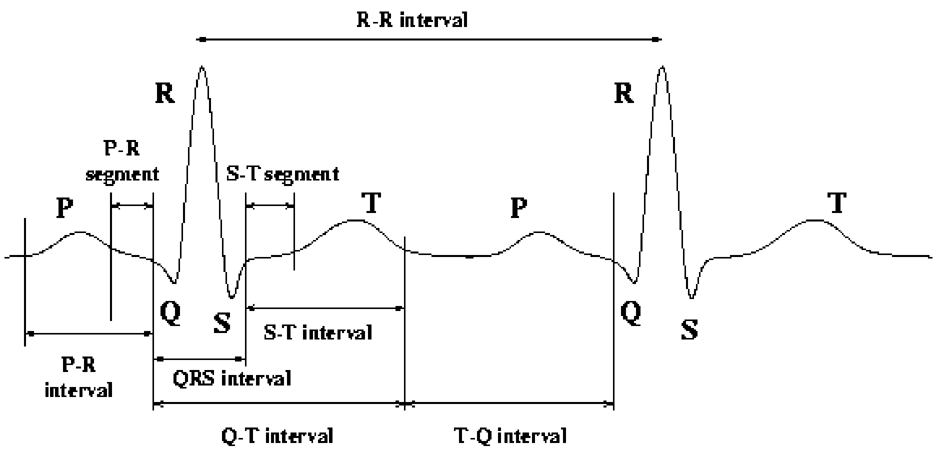


Fig. 2: ECG Waveform [4]

1.2 Discrete Wavelet Transform (DWT)

Wavelet analysis is done by sub sampling of the signal into scaled and shifted versions of the corresponding mother wavelet. It maintains time-frequency components of a signal at instinct resolution and scales. Noise from the noisy ECG signal can be removed using wavelet analysis. The DWT is done using high pass and low pass filter at distinct time domain [6]. The discrete wavelet transform (DWT), provides sufficient information both for decomposition and reconstruction of the original signal, with reduction in the computation time. In this work, DWT is applied on filtered ECG signal to explore the signal features. Here two levels DWT is applied using sym6 function. The function divided the signal in High and low frequency bands. The information preserving signal exploration is performed using sym6. The basic model of DWT process is shown in figure 3.

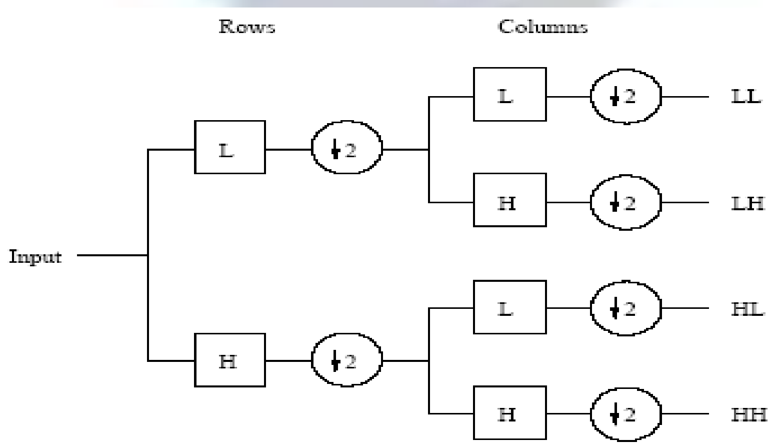


Fig 3: Discrete wavelet transforms [6]

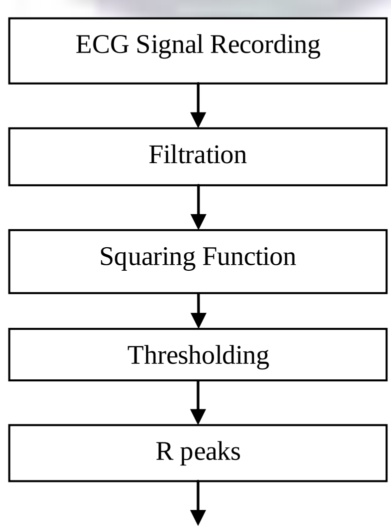
2. LITERATURE REVIEW

Various techniques or methods have been introduced till now for the diagnosis of sleep apnea disorder. Various statistical features and characteristics of distinct signals such as the thorax and abdomen effort signals oxygen saturation [25], nasal air flow, electroencephalogram (EEG), acoustic speech signal, electrocardiogram [ECG] are mainly used for the identification of sleep apnea features to detect sleep apnea [7].In 2004 P de Chazal et al [8] introduced a technique which automatically investigates the happening of epochs of sleep apnea from the ECG signal. The linear Discriminates classifier model has been used for the classification of features of Philipps-University database of sleep apnea. In 2007 M. O. Mendez et al [9] introduced a bivariate autoregressive model with K-Nearest Neighbor (KNN) classifier for the detection of beat-by-beat psd of R peak area of the Physionet database giving accuracy of more than 85% in both training and testing data. In 2009 A H. Khandoker et al [10] proposed the wavelet analysis approach to classify the features of sleep apnea affected ECG signal recordings. The author used the two staged feed forward neural network model giving accuracy of about76.82% .A.F. Quiceno-Manrique et al [11] used HRV analysis for classification of features of sleep apnea affected ECG signal. The author extracted features in dynamic domain from the frequency time distributions for the detection and analyzing obstructive sleep apnea with the help of ECG signals.

In 2010 Sidik Mulyono et al [12] introduced a regression model to examine sleep apnea disorder with the help of principal component regression (PCR) analysis giving accuracy of 79.5%. In 2011 Sani M. Isa et al [13] applied Principal Component Analysis (PCA) classifier on ECG signals for diagnosis of sleep apnea. Majdi Bsoul et al [14] in 2011 proposed 'Apnea Med Assist" system for diagnosing obstructive sleep apnea which was implemented on the smart phones based android platform giving sensitivity of approx 96%.In 2012 Laiali Almazaydeh et al [15] introduced an automated classification algorithm which determines events of short duration of ECG data. This algorithm used Support Vector Machines (SVM) as a classifier for classification of features of apnea affected data which was taken from Physionet database of Apnea ECG signals providing accuracy of approx 96.5%. In 2012 Baile Xie et al [16] applied 10 machine learning algorithms to detect real time hypopnea and sleep apnea syndrome based on electrocardiograph signal recordings and saturation of peripheral oxygen (SpO_2) signals, in combination as well as individually. The author introduced a combination of classifiers to enhance the performance of features classification on Apnea Database obtained from St. Vincent's University College/ University Hospital Dublin providing accuracy of approx 82%. In 2013 S. Khemiri et al [17] introduced a new automatically approach based on analysis of respiratory rate to detect sleep apnea with the help of respiratory and ECG signal recordings. In 2014 Lili Chen et al [18] defined a work on automatic screening for sleep apnea identification by analyzing the ECG signal. Author diagnoses the signal under multiple channels of physiological signal and perform the segmented event analysis to identify the occurrence of disease over the signal and obtained accuracy of about 92% approx.

3. MATERIAL & METHODS

The presented work is to extracting the features of sleep apnea disorder over the ECG signal and which are used to detect the abnormal pauses in breathing during sleep. For this purpose a feature adaptive approach is defined to extract the features of sleep apnea affected ECG signal disorder over the ECG signal. The systematic block diagram of the proposed algorithm is shown in figure 4.



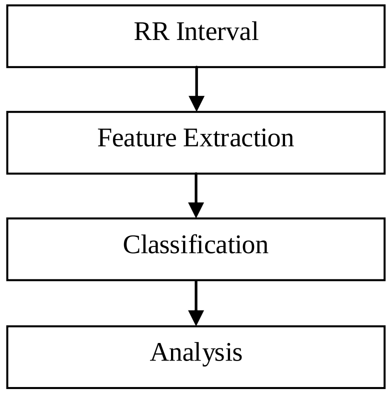


Fig. 4: Schematic Diagram of the system

3.1 Database

The dataset used is collected from https://www.physionet.org/physiobank/database/apnea ecg [19]. This dataset has collected the ECG signal instances on different events recorded on two consecutive nights. These collected ECG signals are digitized at 200Hz and later decimated to 100 Hz to obtain the consistency over the signal. The dataset is having 23 signals with two recording of each.

3.2 Filtration Process

For the filtration process high pass filter and discrete wavelet transform have been used

- **High Pass Filter**

The high pass filter diminishes the influence of low frequency noise (baseline wander) [20]. At the early stage of the work, the ECG signal impurities are removed i.e. baseline drift has been removed using 2nd order IIR Butterworth high pass filter which has been designed with cut off frequency(fc) of 10 Hz and sampling rate (fs) of 100 Hz which gives normalized cutoff frequency of filter 0.1.

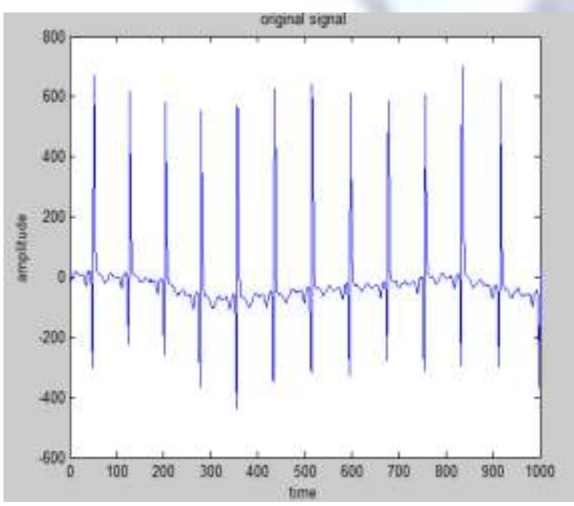


Fig. 5: Original ECG Signal

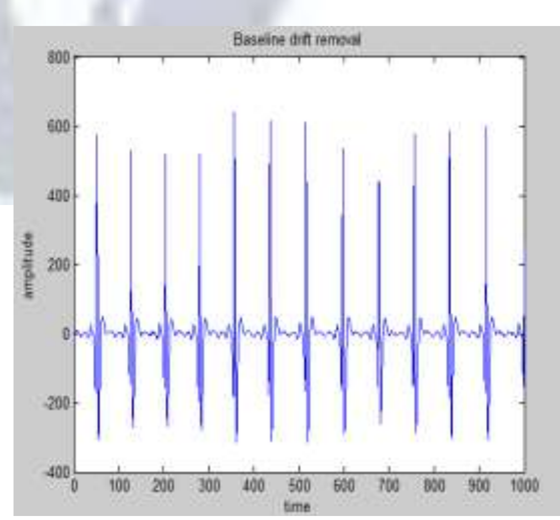


Fig. 6: Baseline Drift Removal

- **Discrete Wavelet Transform**

After removal of baseline drift, double Discrete Wavelet Transform (DWT) over the ECG has been applied with sym6 mother wavelet to remove the signal impurities and noise [21]. The symlet mother wavelets are considered as the modified symmetrical version of the Daubechies mother wavelet family with similar properties.

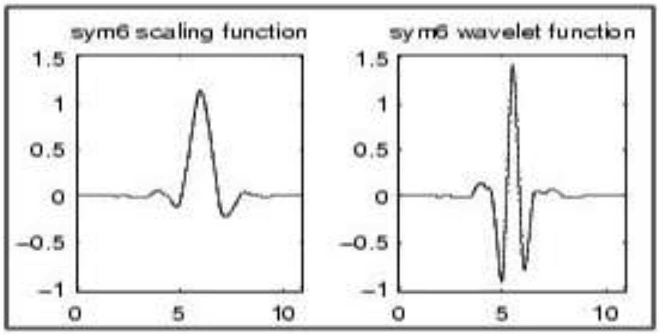


Fig.7: Symlet6 Mother Wavelet [21]

3.3 Squaring

After obtaining clean ECG signal squaring operation has been applied on the signal point by point to get the square wave signal with the equation as

$$y(nT) = [x(nT)]^2 \qquad (1)$$

By squaring the signal function all points become positive and gives almost required ECG signal frequencies i.e. high frequencies.

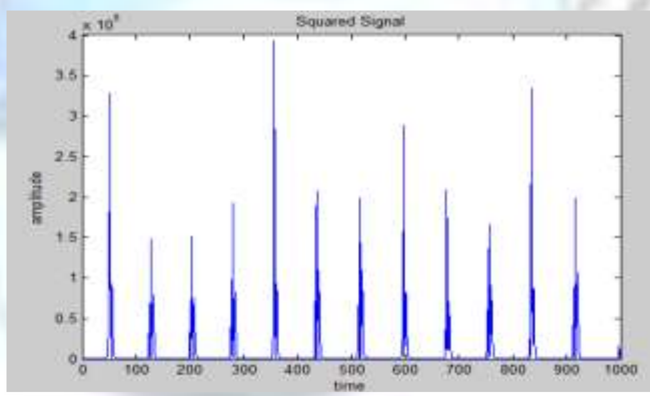


Fig. 7: Squared Signal

3.4 Thresholding

To detect the R peaks thresholding has been applied on the squared signal

Threshold= (max_value – min_value)/3 (2)

3.5 R-peaks

After applying thresholding we have got the R-peaks of the ECG signal recordings which is the local maxima within the time interval of 150ms.Once the R-peaks were obtained RR interval has been determined which is the time interval between two consecutive R-peaks [25].

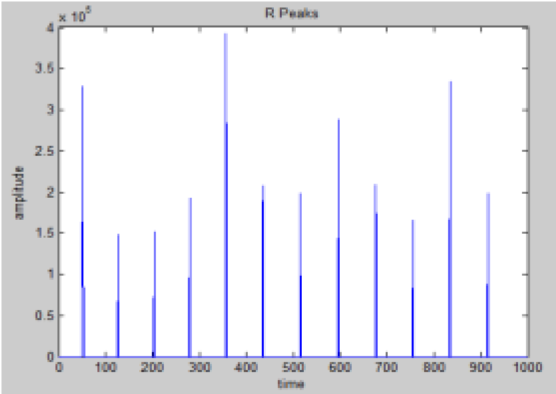


Fig. 8: R- peaks detected

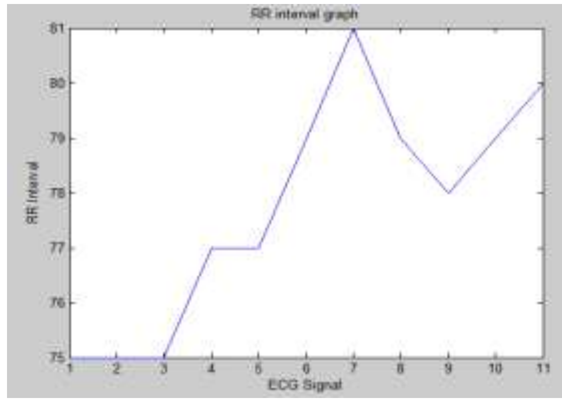


Fig. 9: RR interval plot

```
rrinterval =

    75    75    75    77    77    79    81    79    78    79    80
```

Fig. 10: RR intervals

3.6 Feature Extraction

After obtaining RR interval the ECG signal recording features have been extracted which are very effective in determining sleep apnea. In this work, different types of features are collected to generate the feature set. Based on this feature set, the actual recognition and classification process is performed. The feature extraction is here been defined under specification of fix segments as well as RR interval specific analysis. The features collected in this work to perform the effective signal analysis which are considered to be highly related with sleep apnea are:

- Segmented mean of fix interval or the range
- Segmented standard deviation of fix interval or the range
- Segmented Peak
- Variance of fix interval or the range
- Mean square error of segment and RR interval recording
- mean absolute error of segment and RR interval recording
- Amplitude standard deviation of RR interval recording
- Median of RR interval recording

3.7 Support Vector Machine (SVM)

SVM is the classifier used in this work to identify the apnea and normal instances. This classifier is able to provide the high accuracy in classification process while working with high dimensional data [26]. SVM classifier actually comes under kernel based algorithmic approaches. In this approach, the data dependency is also identified as the functional computation to generate the feature space. The linear kernel specification is here defined to control the classification process. We have separated data into 80 % for training dataset and 20 % for testing dataset and then classification is applied.

4. RESULTS

We have implemented our proposed model in MATLAB using physionet apnea ECG database. We have calculated the Accuracy to analyze the performance of our proposed model.We have obtained an accuracy of 93% with our proposed model by applying it on 1 min apnea ECG database.

Properties	Values
Total Positive (Apnea)	20
True Positive (Identified)	19
True Positive Rate	95%
False Positive	1
False Positive Rate	5%

Table I: Apnea Identification

Properties	Values
Total Positive (Normal)	10
True Positive (Identified)	10
True Positive Rate	100%
False Positive	0
False Positive Rate	0%

Table II: Normal Identification

References	**Year**	**Classifier**	**Accuracy**
Mendez [9]	2007	KNN	85%
Marcos[21]	2009	QDA,LDA,KNN,LR	87.61%
Khandoker[10]	2009	SVM	92.80%
Alvarez [23]	2010	LR	90%
Varon[24]	2013	LS-SVM	86%
Chen[18]	2014	SVM	92.8%
Our Study	**2015**	**SVM**	**93.00%**

Table III: Comparison with other techniques

5. CONCLUSION

The proposed algorithm has been implemented in MATLAB environment and applied on 1 min physionet ECG apnea dataset. The features included in this work are based on RR interval and segment generation. The SVM classifier with the help of linear kernel function has been applied to perform the classification for apnea and normal signal which gave accuracy of approx. 93%
.

REFERENCES

[1]. "Sleep Apnea: What Is Sleep Apnea?". NHLBI: Health Information for the Public. U.S. Department of Health and Human Services.
[2]. J. Stanley, Sleep Disorder Overview, Available at: http:// www.healthcommunities.com / sleep-disorders / overview of sleep disorders.html (Online)
[3]. S. Redline, "Sleep Apnea: Key Points". Available at: http: //www.nhlbi.nih.gov/health/health-topics/topics/sleepapnea
[4]. Dr. Nicholas G. Tullo,(may 2015), ECG tutorial, Available at: https: // www . ecgacademy.com/aboutUs.html
[5]. School of Health Sciences, Physiology and Anatomy of the Heart by The University of Nottingham, UK, Available at: http: // www. Nottingham .ac.uk /nursing /practice /resources /cardiology/function/anatomy.php
[6]. R.Polikar, The Wavelet Tutorial, Available at : http ://users .rowan .edu / polikar/Wavelets/WT.html
[7]. T.I. Morgenthaler, V. Kagramanov, V. Hanak, P.A.Decker, "Complex sleep apnea syndrome: is it a unique clinical syndrome?", in Sleep, vol. 29,no. 9,pp. 1203–1209, Sept. 2006.
[8]. P. Chazal, T. Penzel and C. Heneghan,"Automated Detection of Obstructive Sleep Apnoea at Different Time Scales Using the Electrocardiogram," Institute of Physics Publishing, vol. 25, no. 4, pp. 967-983, Aug. 2004
[9]. M. Mendez, D. Ruini, O. Villantieri, M. Matteucci, T. Penzel and A.Bianchi, "Detection of Sleep Apnea from Surface ECG Based on features Extracted by an Autoregressive Model ," in Proceedings of the IEEE International Conference on Engineering in Medicine and Biology Society [EMBS 2007], pp. 6105-6108, Aug. 2007
[10]. A. H. Khandoker, J. Gubbi, M.Palaniswami, " Automated Scoring of Obstructive Sleep Apnea and Hypopnea Events Using Short-Term Electrocardiogram Recordings," in IEEE Transactions On Information Technology In Biomedicine, vol. 13, no. 6, pp 1057-1067, Nov. 2009
[11].A.F. Quiceno-Manrique, J.B. Alonso-Hern´andez, C.M. Travieso-Gonz´alez," Detection of obstructive sleep apnea in ECG recordings using time-frequency distributions and dynamic features," in Proceedings of the IEEE31st IEEE Annual International Conference on Engineering in Medicine and Biology Society [EMBS 2009],pp. 5559-5562, Sep. 2009.
[12]. S. Mulyono, S. M. Isa, M. I. Fanany, W. Jatmiko, and T. Basaruddin, " Principal Component Regression Analysis on Automatic Sleep Apnea Detection from ECG Data,"in ICACSIS 2010, ISSN: 2086-1796,pp 193-198, 2010

[13]. S. M. Isa, M. I. Fanany, W. Jatmiko, A. M. Arymurthy, "Sleep Apnea Detection from ECG Signal: Analysis on Optimal Features, Principal Components, and Nonlinearity," in Proceedings of the 5th IEEE International Conference on Bioinformatics and Biomedical Engineering [iCBBE 2011], pp. 1-4, 2011.

[14]. M. Bsoul, H. Minn and L. Tamil, "Apnea MedAssist: Real-time Sleep Apnea Monitor Using Single-Lead ECG," in IEEE Transactions On Information Technology In Biomedicine, vol. 15, no. 3, pp 416-427, May 2011.

[15]. L. Almazaydeh, K. Elleithy, M. Faezipour, "Detection of obstructive sleep apnea through ECG signal features," Electro/Information Technology [EIT], 2012 IEEE InternationalConference on 6-8 May 2012.

[16]. B. Xie, H. Minn, "Real Time Sleep Apnea Detection by Classifier Combination," in IEEE Transactions on Information Technology in Biomedicine,vol16,no.3,pp.469-477,May 2012.

[17]. S. Khemiri, K. Aloui, and M Saber. Naceur, "Detection of Sleep Apnea in SWS Stages Using ECG Signal,"in 3rd International Conference on Image Processing and Electronics Engineering (ICIPEE'2013) Dec. 25-26, 2013 Bangkok (Thailand).

[18]. L.Chen, X. Zhang, and C. Song , "An Automatic Screening Approach for Obstructive Sleep Apnea Diagnosis Based on Single-Lead Electrocardiogram", IEEE Transactions On Automation Science And Engineering,vol.12,no.1,pp.1-10,2014.

[19].Physionet, Data for development and evaluation of ECG based Apnea detectors, Available at: http://www.physionet.org/physiobank/database/apnea-ecg/.

[20]. J. Hopkins, Electrocardiogram, Available at: http: //www. Hopkinsmedicine .org/ health library /test _procedures /cardiovascular/electrocardiogram_92,P07970/.

[21]. G, Cornelia, R. Romulus, "ECG Signal Processing using Wavelets", March2011.

[22]. J. V. Marcos, R. Hornero, D. Álvarez, F. del Campo, and C. Zamarrón, "Assessment of four statistical pattern recognition techniques to assist in obstructive sleep apnea diagnosis from nocturnal oximetry," Med.Eng. Phys., vol. 31, no. 8, pp. 971–978, 2009.

[23]. D. Alvarez, R. Hornero, J. V. Marcos, and F. del Campo, "Multivariate analysis of blood oxygen saturation recordings in obstructive sleep apnea diagnosis," IEEE Trans. Biomed. Engg., vol. 57, no. 12, pp. 2816–2824, 2010.

[24]. C. Varon, D. Testelmans, B. Buyse,J. A.K. Suykens and S. V. Huffel, "Sleep apnea classification using least-squares support vector machines," ," in Proceedings of 35 IEEE Annual International Conference on Engineering in Medicine and Biology Society [EMBC 2013],pp. 5029 – 5032,2013.

[25]. A.Laiali, K.Elleit hy, and M.Faezipour. "Obstructive sleep apnea detection using SVM-based classification of ECG signal features ", 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2012.

[26]. Support Vector Machine, Available at: https: //en.wikipedia.org/ wiki/ Support _ vector_machine.