SLEEP APNEA DETECTION USING PHYSIOLOGICAL SIGNALS

Rekha S[1], Dr. Shilpa R[2]

[1]M.tech Student, Dept of ECE, VVCE, MYSURU
[2]Associated Professor, Dept of ECE, VVCE, MYSURU

Abstract—*Sleep apnea is one of the hypothetically serious sleep disorder in which breathing frequently stops and starts. The undiagnosed sleep apnea can be very severe and hence rapid drops in blood oxygen level could occur during which could increases possibility of advanced insulin resistance and type 2 diabetes. However, several people are unaware of their condition. The typical for diagnosing sleep is an overnight polysomnography (PSG) in a committed sleep laboratory. Since, these tests are costly and beds are limited as educated staff needs to analyze the complete according. An automatic detection method would permit a quicker diagnosis and more patients to be analyzed. Hence detection of sleep apnea is compulsory so that it could be treated. This study established an algorithm that a short term event extraction from Electrocardiography (ECG) signal and combining neural network methodologies for automated detection of sleep apnea. This study gives visual experiences to the users by visual parameters such HRV measurements, Poincare plot, Global and Local return map. This helps the Doctor analyze whether the person is suffering from sleep apnea or not.*

Key Words: Sleep-apnea, Physiological signal, RR-intervals, Heart-rate-variability measurement, neural network.

1 INTRODUCTION

Sleep apnea is one of the most related sleep disorders and is characterized by breathing pauses occurrence, also identified as apneaic event, at night which leads to recurrent awakenings [1]. It is naturally classified as either obstructive sleep apnea (OSA) or central sleep apnea (CSA).In obstructive sleep apnea is mutual kind of sleep apnea which is affected by complete or partial obstructive of higher airway and characterized by continue episodes of shallow or paused breathing during sleep and decrease in blood oxygen saturation. In central sleep apnea occurs when the brain does not guide the signals which are needed to breath. Sleep apnea is diagnosis using devices like continuous positive air pressure (CPAP) machine, Overnight Pulse Oximetry and Unattended Portable Monitors. Untreated or undiagnosed sleep apnea can lead to serious complication like danger of hypertension, cardiac arrhythmia, heart attack and diabetes cancer and strokes [2, 3]. Some of the studies are report that an estimated 49.7% of male and 23.4% of female adults suffer from sleep disordered breathing, many cases remain undiagnosed as patients are rarely aware of their condition [4].

A sleep apnea is diagnosed by overnight polysomnography (PSG) recording at particular sleep laboratory. This PSG records the cardiovascular functioning, oxygen saturation, sleep status and multiple physiological signals like ECG, PPG and EMG. Then using the references of standard such as American Academy of sleep medicine (AASM) [5] under the guidelines trained sleep technical analyses the data of overnight and estimates each fragment of the signals. Each fragment of the signal is then noted as either OSA or CSA. Apnea-Hypopnea-Index (AHI) represents the number of apnea and hypopnea measures per hour and used to categorize patient into normal, moderate or severe class. Due to limited quantity of beds for PSG recording and the limited quantity of trained technicians for examination waiting times will be extremely long. The time taken to record ranges between 2 to 10 months in UK and in between 7 to 60 months in USA [6]. In order to raise the total of the people that can be analyzed and to reduce higher intra and inter-scorer variability [7].The study need to assist the automated methods of sleep technicians have stayed explored.

The wavelet transform is additional thought-provoking method aimed for extracting waveform information in which frequency resolution is good at lower frequency and time resolution is high at higher frequency. In automatic waveform detection is standard in wavelet based method which is compared to a threshold for spike extraction.

In this work, a sleep apnea detection method is proposed, based on a short term event extraction from ECG signal and combining neural network methodologies for automated detection of sleep apnea. By using the raw physiological respiratory signals such as ECG signal, which automatically learn and extract relevant feature and detects the potential sleep apnea events.

2 RELATED WORK

2.1 Physiological signal

The sleep apnea diagnosis is done by using several physiological signals such as ECG, EMG and PPG signals by considering as input data. There are many devices to diagnosis the sleep apnea like pulse oximetry, polysomnography and Unattended Portable Monitors. Analysis of those extents provides physicians with important physiological information that may help them to uncover fundamental dynamics of human health. It also allows them to determine patient health state and choose the right treatment. Respiration rate (RR) interval is stately by the difference in the beat-to-beat intervals which is identified as "variability of cycle length" or "variability of RR". Where R is a point resultant to the peak of QRS complex of ECG wave and RR is the interval between continuous. More definitely, the apnea period announces a frequency element to the RR interval tachogram, which resemble to the apnea duration. Heart rate variability (HRV)has develop a appreciated non-invasive tool of measuring the state of cardiovascular autonomic role in the last decades and it has been frequently used in the analysis of physiological signals in the various clinical and functional situation .Over the recent years there was interest in heart rate nursing without electrodes.

2.2 Sleep apnea detection

The sleep apnea effects were lead on human heart constructed in electrical activity which is recorded [8].The sleep is analyzed different types of sleep apnea were detected such as obstructive sleep apnea and central sleep apnea.

Several algorithms have been industrialized to detect sleep apnea automatically by using one or two physiological signal which is diagnosed by polysomnography device. In adult's sleep apnea were detected using overnight pulse oximetry and unattended portable monitors.

However, various methods had been used in detecting sleep apnea in which collective approach is used to interpret rule based algorithms which gives information of certain epoch signals and identified as having a sleep apnea or not [9]. Several approach have been commonly used such as machine learning, kernel nearest neighbors (KNN), support vector machine (SVM) and artificial neural network (ANN).

3 PROPOSED METHODOLOGY

The sleep apnea diagnosis is done using polysomnography in sleep laboratory. Since the tests are expensive and limited beds more number of patients cannot be analyzed. These proposed methodologies can faster diagnosis and also the more number of patients can analyze in which automated detection of sleep apnea by short term event extraction from physiological signals (ECG/PPG) and combining back propagation in neural network method. The ECG/PPG signals are loaded simultaneously. First the person is tested by taking ECG signal as input data. If the person does not have sleep apnea then testing is stopped. If person is suffering from sleep apnea then testing done using PPG signal as input data to validate.

The automated sleep apnea detection by physiological signals such as ECG and PPG signals are considered in this study. These physiological signals were trained using neural network and tested using by the real time data.

Figure1. Illuminates to achieve the method for detection of sleep apnea initially physiological signal are trained, in which physiological data were collected from the physio-net database. By using notch filter 50HZ noise frequency is removed and wavelet transform is used to extract the features from physiological signal and used back propagation method in neural network which classifies the Non -sleep disorder and sleep disorder. The testing is done by using real time data in which gives the visualize output by graphical user interphase.

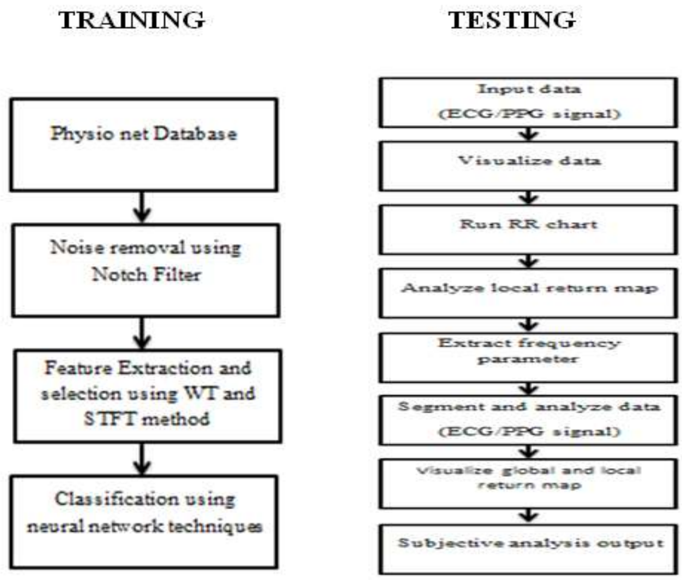


Figure-1: Block diagram for sleep apnea detection.

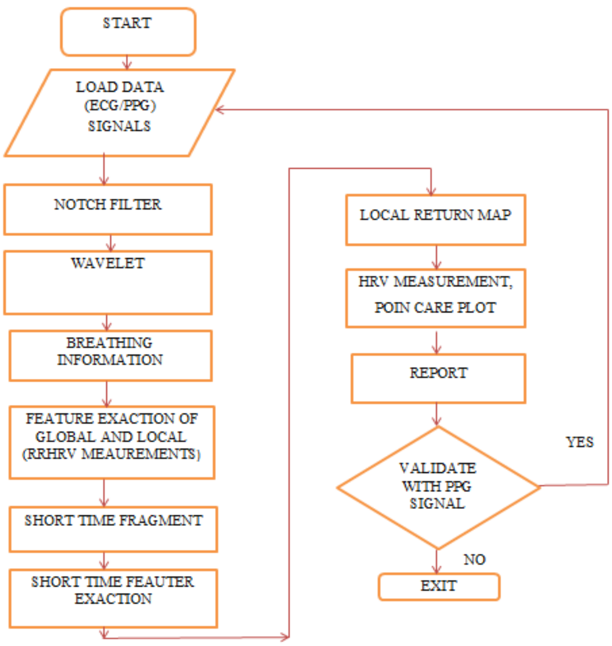


Figure-2: Flow chart of sleep apnea detection.

Step 1: Data loaded

The real time data of the patient is collected. The obtained data which is in analog form is converted into digital from.

Initially ECG data is consider as input data and loaded.

Step 2: Notch filter

The notch filter is used to remove the 50HZ noise frequency in ECG signal with the sampling frequency of 1000HZ. The nyquist frequency is 500HZ, and notch filter to nyquist ratio is 0.1.

Step 3: Wavelet

A wavelet transform technique analyzes the noise present in ECG signal such as power line interferences and baseline wander noises are removed by wavelet DB6.

Step 4: Breathing information

The breathing rate is measure of heart rate in which the number of times the heart beats per minute.

Step 5: Global and local return map feature are extraction

The HRV measurements are obtained and differentiated for both local and global return map.

Step 6: Short time fragmentation

The ECG signal waveform is broken into desired range and the functions of each smaller segment are identified.

Step 7: Local return map

This map foregrounds the occurrences of sleep apnea by the nodes representation. If the nodes are closely spaced then sleep apnea is not present. If the nodes are randomly spaced then sleep apnea is present.

Step 8: HRV measurements and Poincare plot

The HRV measurements of various factors are obtained and displayed both in global and local return map.

The Poincare plot analysis is made in the global return map which identifies the RR interval. HRV increases when the values are greatly spread while HRV decreases when the values are lesser spread in global return map.

Step 9: Report

The obtained HRV measurement, visualize analyzes the global and local return map output that are given to Doctor. The Doctor checks the output and confirms whether the person is suffering from sleep apnea or not.

Step 10: Validate with PPG

If the Doctor found that patient is suffering from sleep apnea disorder using the ECG signal, once again test for sleep apnea is conducted using PPG signal.

4 RESULTS AND DISCUSSION

In this study the automatic detection of sleep apnea by short time event extraction from ECG/PPG signals which are trained by the neural network using Matlab software. The obtained results are represented by graphical user interphase. If the person comes to known that is suffering from sleep disorder (sleep apnea) then Doctor informs to diagnose using PPG signal.

This study gives visual experience to the user by visual parameters such as HRV measurements, Poincare plot, global and local return maps.

The below simulation gives the output results of non-sleep disorder, sleep disorder using ECG signal and also PPG signal if the person is suffering from sleep disorder (sleep apnea).

Table- 1:Non-sleep apnea HRV measurements of ECG signal.

Non-sleep apnea HRV measures [ECG signal]		
	Global return map	**Local return map**
SDNN	**0.3**	**0.2**
PNN50	**0.0**	**0.0**
RMSSD	**0.0**	**0.0**
TRI	**1.0**	**1.0**
SD1|SD2	**0.0|0.5**	**0.0|0.3**
LF|HF	**57.8|42.2**	**58.5|41.5**
SD1/SD2 ratio	**0.04**	**0.06**
LF/HF ratio	**1.37**	**1.41**
TINN	**16**	**16**
Shift	**(-0.00,-0.00)**	**(0.00,0.00)**
IQR	**0.77**	**0.61**
RR HRV median	**0.90**	**0.75**
Mean RR|HR	**2|3.0325**	**2|2.5866**

The table1 represents non-sleep apnea HRV measurements by taking ECG signal as input data and compares the global and local return map.

Table-2: Sleep apnea HRV measurements of ECG signal.

Sleep apnea HRV measures [ECG signal]		
	Global return map	Local return map
SDNN	24.2	29.3
PNN50	0.0	0.0
RMSSD	6.6	7.8
TRI	3.4	2.3
SD1|SD2	4.6|33.8	5.5|40.7
LF|HF	29.42| 70.58	NaN| NaN
SD1/SD2 ratio	0.14	0.13
LF/HF ratio	0.417	NaN
TINN	47	31
Shift	(+0.22,+0.16)	(+0.23,+0.12)
IQR	2.58	2.49
RR HRV median	2.56	2.83
Mean RR|HR	48|1.244	48|1.246

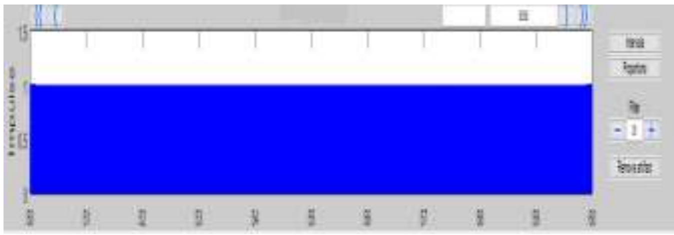
The table 2 represents sleep apnea HRV measurements by taking ECG signal as input data and compares the global and local return map.

Table -3: Sleep apnea HRV measurements of PPG signal.

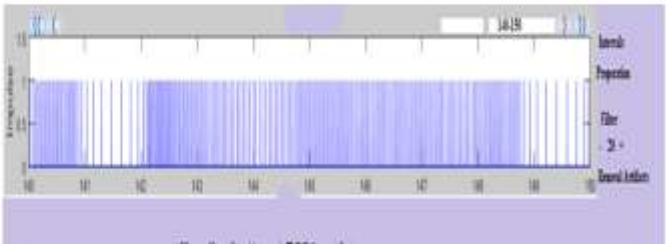
Sleep apnea HRV measures [PPG signal]		
	Global return map	Local return map
SDNN	0.5	0.3
PNN50	0.0	0.0
RMSSD	0.0	0.0
TRI	1.0	1.0
SD1|SD2	0.0|0.7	0.0|0.5
LF|HF	64.9|35.1	42.4|57.6
SD1/SD2 ratio	0.01	0.02
LF/HF ratio	1.85	0.74
TINN	16	16
Shift	(+0.00,+0.00)	(0.01,0.01)
IQR	0.71	1.00
RR HRV median	0.81	1.13
Mean RR|HR	2|3.6173	1|5.0230

The table 3 represents sleep apnea HRV measurements by taking PPG signal as input data and compares the global and local return map.

(a)



(b)



(c)

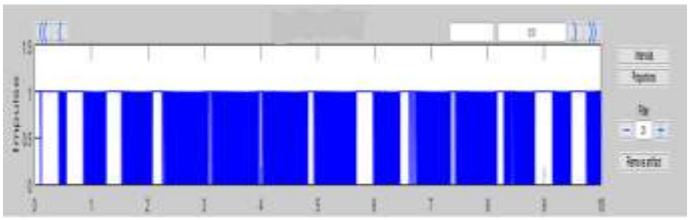
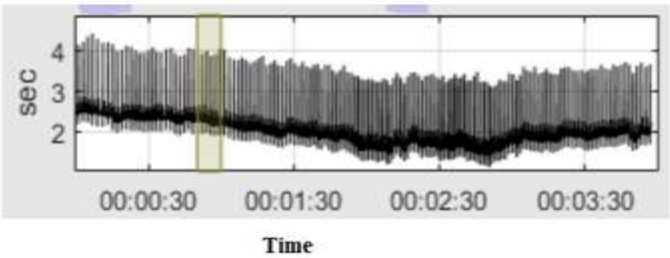
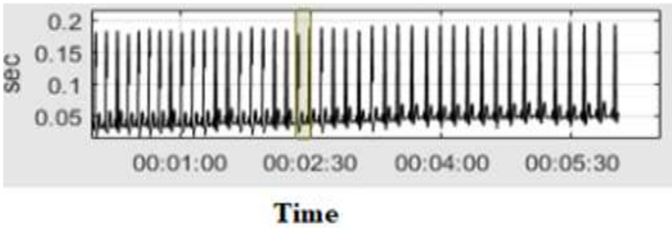


Figure-3: Illustration input data of person. (a) ECG input data for non-sleep apnea waveforms of breathing represent zero fluctuations. (b) ECG input data for sleep disorder represents fluctuations at certain point of sleep duration. (c) PPG input data for sleep apnea represents fluctuation at certain point of sleep duration.

(a)



(b)



(c)

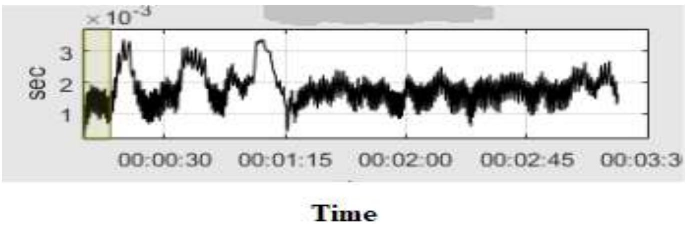
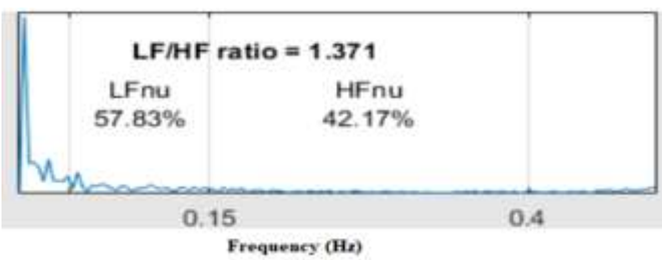
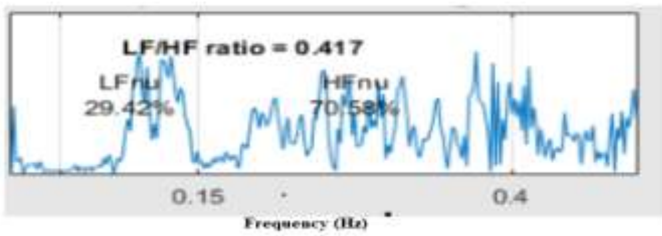


Figure-4: Illustration the RR tachogram which further encloses the mean RR and HR intervals, low and high frequencies. (a) The RR tachogram for non-sleep apnea has long RR and HR intervals and low and high frequencies values are 57.83 and 42.2 percentages respectively. (b) The RR tachogram for sleep apnea found that drastic increased in RR interval and decreased in HR interval values and obtained decreased low frequency i.e. 29.42 percentage and increased high frequency i.e. 70.58 percentage.(c) The RR tachogram which is further encloses the mean RR and HR intervals, low and high frequencies for sleep disorder by given PPG signal. RR tachogram for sleep apnea using PPG signal as input data it is found that RR interval is 2.00 and HR interval is 3.6173. Similarly lower and higher frequencies values are 64.9 and 35.1percentage respectively.

(a)



(b)



(c)

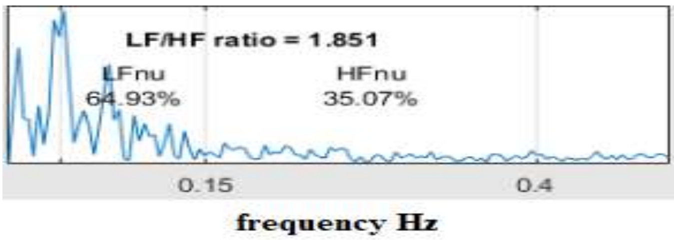
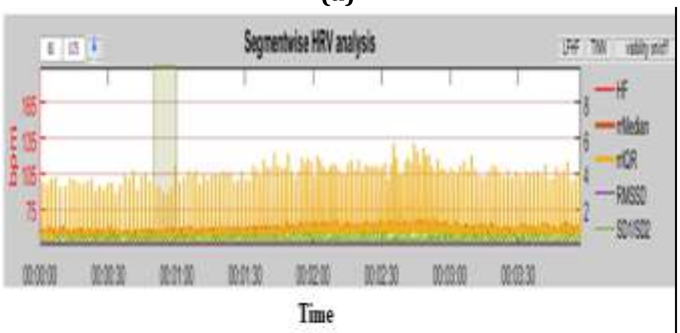
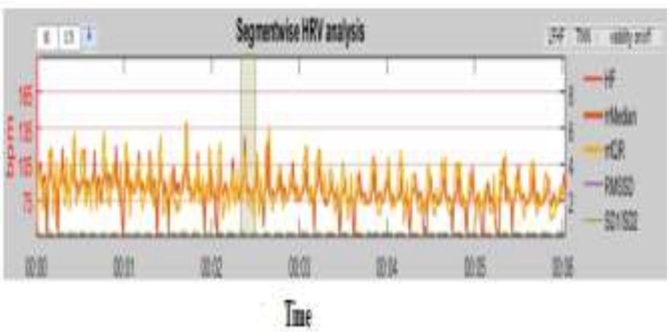


Figure-5: Illustration the spectrum analysis of RR tachogram. (a) Spectrum analysis of RR tachogram for non-sleep apnea that implies low frequency to high frequency ratios value is1.371. (b) Spectrum analysis of RR tachogram for sleep apnea that implies low frequency to high frequency ratios value is 0.412. (c) Spectrum analysis of RR tachogram for sleep apnea by PPG signal as input that implies low and high frequency ratio value is 1.85.

(a)



(b)



(c)

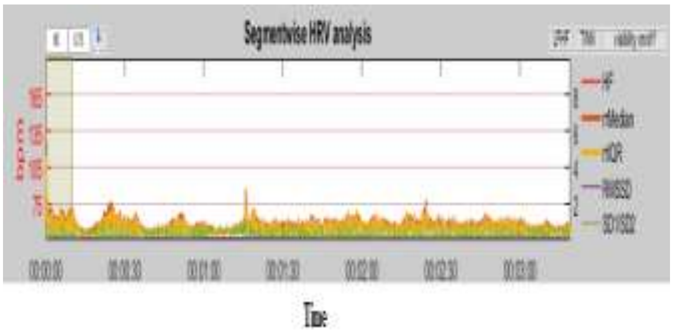
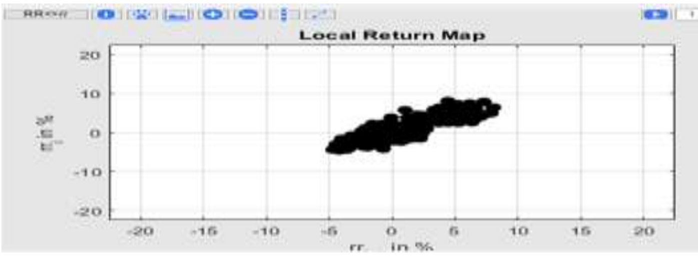
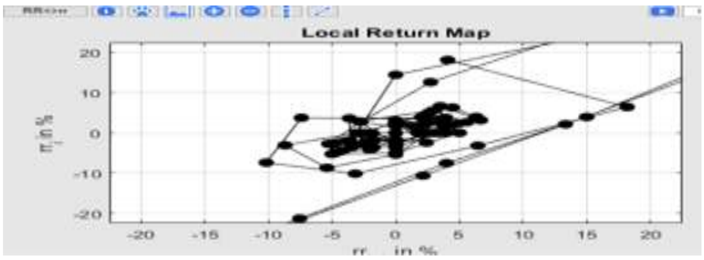


Figure-6: Illustration segmented HRV analysis. (a) ECG signal segmented HRV analysis for non-sleep apnea in which TINN is 16. (b) ECG signal segmented HRV analysis for sleep apnea in which TINN is 47. (c) PPG signal segmented HRV analysis for sleep apnea in which TINN is 16.

(a)



(b)



(c)

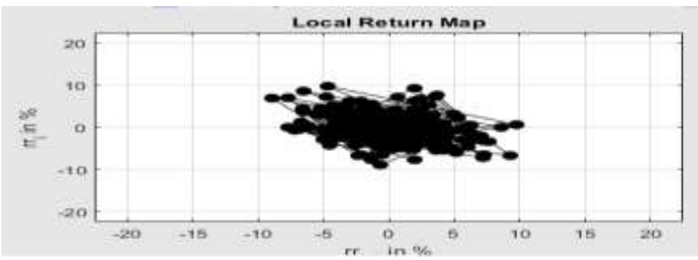
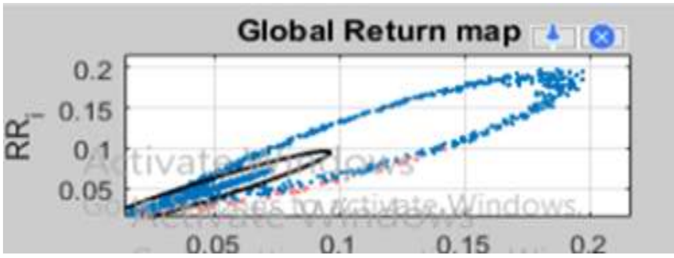


Figure-7: Displays local return maps. (a) Local return produces the information regarding the each RR interval predictions for non-sleep apnea in which the heart rate variability is 0.75 and nodes are closer. (b) local return produces the information regarding the each RR interval predictions for sleep apnea in which heart rate variability is 2.83 and nodes are farer.(c) Displays PPG signal local maps provides the information regarding the each RR interval predictors for sleep disorder nodes are also far and heart rate variability is 1.13.

(a)

(b)



(c)

Figure-8: Displays global map Poin care plot. (a) Poincare plot produces the information regarding entire RR intervals for non-sleep apnea in which the heart rate variability is 0.90.

(b)Poincare plot produces the information regarding entire RR intervals for sleep apnea in which the heart rate variability is 2.56. (c) Displays PPG signal imputed poin care plot global map produces the information regarding entire RR interval for sleep disorder in which the heart rate variability is 0.81.

5 CONCULSION

The proposed work develops an algorithm that demonstrates short time event extraction from ECG signal and combining neural network methodology for automated detection of sleep apnea. This study can analyze whether the person is suffering from sleep apnea or not. If the person is not suffering from sleep apnea then further diagnosis is not required. If the person is suffering from sleep apnea then further diagnosis is done using PPG signal to validate. The proposed work gives subjective information which helps Doctor to find out whether the person is suffering from sleep apnea or not.

REFERENCES

[1] C. Guilleminault, A. Tilkian, and W. C. Dement, "The sleep apnea syndromes," Ann. rev. of medicine, vol. 27, no. 1, pp. 465–484, 1976.

[2] V. K. somers, d. p. white, r. Amin, W. T. Abraham, F. Costa, S. Daniels, J.S. Floras, C.E. Hunt, L. J. Olson, and Others, "Sleep aplnea and cardiovasular disease," Circulation, vol.118, no, 10,pp . 1080-1111-2008.

[3] H. K. Yaggi, J. Concato, W. N. kernan, J. H. Lichtman, L. M. Brass, and V. Mohsenin, "Obstructive sleep apnea as arisk for stoke and death," new Engalnd journal of medicine, Vol. 27, no. 19, pp. 2034-2041, 2005.

[4] R. Heinzer, S. Vat, P. Marques-Vidal, H. Marti-Soler, D. Andries, N. Tobback, V. Mooser, M. Preisig, A. Malhotra, G. Waeber et al., "Prevalence of sleep-disordered breathing in the general population: the hypnolaus study," The Lancet Respiratory Medicine, vol. 3, no. 4, pp. 310–318, 2015.

[5] R. B. Berry, R. Brooks, C. E. Gamaldo, S. M. Harding, C. L. Marcus, and B. V. Vaughn, "The AASM manual for the scoring of sleep and associated events," Rules, Terminology and Technical Specifications, Darien, Illinois, American Academy of Sleep Medicine, 2012.

[6] W. W. Flemons, N. J. Douglas, S. T. Kuna, D. O. Rodenstein, and J. Wheatley, "Access to diagnosis and treatment of patients with suspected sleep apnea," American journal of respiratory and critical care medicine, vol. 169, no. 6, pp. 668–672, 2004.

[7] D. Bliwise, N. G. Bliwise, H. C. Kraemer, and W. Dement, "Measurement error in visually scored electrophysiological data: respiration during sleep," Journal of neuroscience methods, vol. 12, no. 1, pp. 49–56, 1984.

[8] C. Guilleminault, R. Winkle, S. Connolly, K. Melvin, A. Tilkian, Cyclical variation of the heart rate in sleep apnoea syndrome: Mechanisms, and usefulness of 24 h electrocardiography as a screening technique, The Lancet 323 (8369) (1984) 126–131.

[9] G.Sannino,I.DeFalco,andG.DePietro,"Anautomaticrules extraction approach to support osa events detection in an mhealth system," IEEE journal of biomedical and health informatics, vol. 18, no. 5, pp. 1518– 1524, 2014.