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Sleep Apnea Identification using ECG and PPG Signals Involving Neural Network

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Abstract: ***Sleep apnea is one of the hypothetically severe sleep disorders that often stops and begins to breathe. The undiagnosed sleep apnea can be very serious, resulting in fast decreases in blood oxygen levels, during which developed insulin resistance and type 2 diabetes may increase. Several people do not know their condition, though. Typical for sleep diagnosis is an overnight polysomnography (PSG) in a dedicated sleep laboratory. Since these exams are expensive and beds are restricted due to the need for trained employees to evaluate the full. An automatic detection technique would allow faster 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 signaled a short-term electrocardiographic event extraction (ECG) and combined neural network methodologies for automatic sleep apnea detection. This study provides users with visual experiences through visual parameters such as HRV measurements, Poincare plot, global and local return map. This enables the doctor evaluate whether or not the individual is suffering from sleep apnea.***

Index Terms: Sleep-apnea, Bio-Medical signals, RR-intervals, Heart-rate-variability measurement, neural network.

I. INTRODUCTION

Sleep apnea is one of the most related sleep disorders and is characterized by breathing pauses occurrence, also identified as apneic 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]. In a particular sleep laboratory, polysomnography (PSG) is classified as a sleep apnea. This PSG records the functioning of the cardiovascular, oxygen saturation, sleep status and various physiological signals such as ECG, PPG and EMG. Then, using conventional references such as the American Academy of Sleep Medicine (AASM) [5] under the rules qualified sleep technique analyzes the night information and estimates each fragment of the signals. Every fragment of the signal is then noted as either OSA or CSA. Apnea-Hypopnea-Index (AHI) is the amount of measurements of apnea and hypopnea per hour used to classify patients into ordinary, moderate or serious classes. Because of the restricted number of beds for PSG recording and because of the restricted number of qualified engineers waiting for exams, it will be incredibly long. The recording time in the UK ranges from 2 to 10 months and in the US from 7 to 60 months [6]. Increase the total amount of people that can be assessed and reduce the higher intra and inter-scorer variability [7]. The research must have been kept exploring the automated techniques of sleep engineers. The wavelet transformation is an extra thought-provoking technique for extracting waveform data in which frequency resolution is good at reduced frequencies and time resolution is high at greater frequencies. In wavelet-based technique, automatic waveform detection is standard compared to a limit for spike extraction. In this study, a technique for sleep apnea detection is suggested, based on a short-term ECG-signal event extraction and combining neural network methodologies for automated sleep apnea detection. By using raw respiratory physiological signals such as an ECG signal that automatically learns and extracts appropriate features and detects prospective occurrences of sleep apnea.

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II. RELATED WORK

A. Biomedical Signal

Sleep apnea diagnosis is performed using several physiological signals, such as ECG, EMG and PPG signals, considered as input information. There are many tools for sleep apnea diagnosis, such as pulse oximetry, polysomnography and unattended portable monitoring. Analysis of these extent offers physicians with significant physiological data that can assist them discover basic dynamics of human health. It also enables them to determine the health status of the patient and to choose the correct therapy.

Respiration rate (RR) interval is characterized by the difference in beat-to-beat intervals recognized as "cycle length variation" or "RR variability". Where R results in the top of the QRS complex of the ECG wave and RR is the interval between the permanent. 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 developed an valued non-invasive tool for assessing cardiovascular autonomy in recent centuries and has been used commonly in the assessment of physiological signals in different clinical and functional situations. There has been interest in heart rate nursing without electrodes over the past few years.

B. Apnea detection of sleep

The consequences of sleep apnea were caused by human core built in electrical activity recorded [8]. Different kinds of sleep apnea have been identified such as obstructive sleep apnea and central sleep apnea.

Several algorithms have been industrialized to automatically identify sleep apnea by using one or two physiological signals diagnosed with polysomnography devices. Using overnight pulse oximetry and unattended mobile monitors, apnea was identified in adult sleep. However, different techniques were used to detect sleep apnea in which a collective method is used to interpret rule-based algorithms that provide data about certain epochal signals and identify as having or not sleep apnea. [9].Several approaches such as machine learning, neighboring kernel (KNN), vector support (SVM) and artificial neural network (ANN) have been frequently used.

III. PROPOSED METHODOLOGY

The diagnosis of sleep apnea takes place in the sleep laboratory using polysomnography. Since the tests are costly and restricted, it is not possible to analyze more patients. These suggested methodologies can be diagnosed more quickly and also more patients can evaluate in which automatic detection of sleep apnea by extraction of short-term events from physiological signals (ECG / PPG) and combining back propagation in neural network technique. The ECG / PPG signals are loaded concurrently. The individual is first tested using the ECG signal as input information. If the individual has no apnea for sleep, the test is halted. If a individual suffers from sleep apnea then tests using PPG signal as input information to validate.

In this study, the automatic identification of sleep apnea by physiological signals such as ECG and PPG are regarded. Using neural network, these physiological signals were educated and tested using real-time information.

Figure1. Initially, physiological signals are trained to accomplish the technique for detecting sleep apnea by collecting physiological information from the physio-net database. Using notch filter 50HZ noise frequency is removed and wavelet transformation is used to obtain characteristics from the physiological signal and reverse propagation technique in the neural network that classifies non-sleep disorder and sleep disorder. The testing is performed using real-time information in which the graphical user interphase visualizes the output.

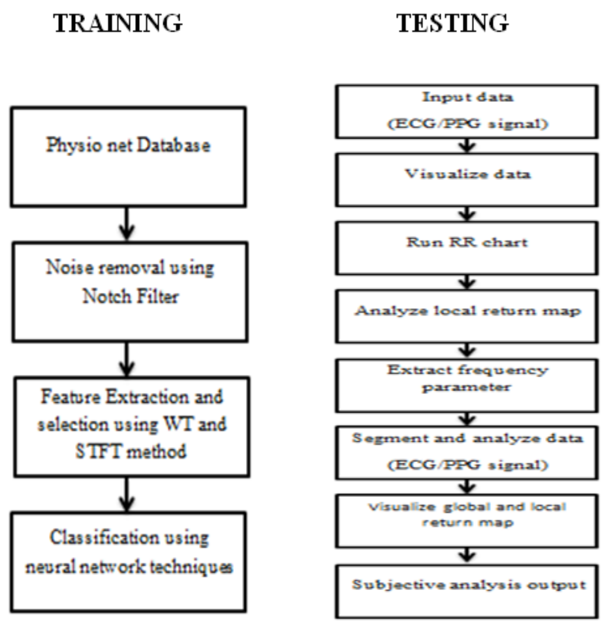

Figure.1:- Block diagram for sleep apnea detection.

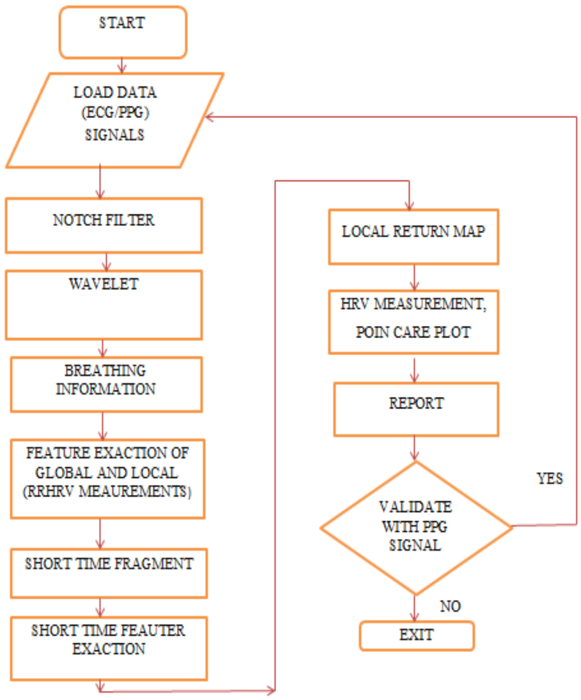

Figure.2:- Flow chart of sleep apnea detection.

Step 1: Data loaded

The patient's actual time information is gathered. The information acquired in analog form is transformed from it into digital. Initially, ECG information is considered and loaded as input information.

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, with a nyquist notch filter ratio of 0.1.

Step 3: Wavelet
A wavelet transform method analyzes the noise present in the ECG signal such as power line interferences, and wavelet DB6 removes baseline wander noise.

Step 4: Breathing information
Breathing pace is a heart rate metric in which the amount of times the heart beats per minute.

Step 5: Global and local return map feature are extraction
The HRV measurements are acquired and distinguished for both local and global return maps.

Step 6: Short time fragmentation
The waveform of the ECG signal is broken into required range and the features of each narrower section are recognized.

Step 7: Local return map
This map emphasizes the occurrence of sleep apnea by the depiction of nodes. If the nodes are tightly spaced, there is no sleep apnea. If the nodes are spaced randomly then there is an apnea for sleep.

Step 8: HRV measurements and Poincare plot
HRV measurements of multiple variables are acquired and presented in both global and local return maps. The Poincare plot analysis is conducted in the global return map that defines the RR interval. HRV improves when values are significantly distributed while HRV reduces when values are less distributed in the global return map.

Step 9: Report
The measurement of HRV acquired visualizes the production of global and local return maps provided to Doctor. The doctor checks the information and confirms whether or not the individual is suffering from sleep apnea.

Step 10: Validate with PPG
If the doctor finds that the patient suffers from sleep apnea disease using the ECG signal, the PPG signal is used to check again for sleep apnea.

IV. RESULTS AND DISCUSSION

In this survey, the automatic identification of sleep apnea by short-term event extraction from ECG / PPG signals trained by the neural network using Matlab software. The outcomes acquired are displayed by the graphical user interphase. If the individual who is suffering from sleep disorder (sleep apnea) becomes known, then the doctor will inform to diagnose using a PPG signal. This study provides the user with visual experience through visual parameters such as HRV readings, Poincare plot, global and local maps of exchange. The simulation below provides the outcomes of non-sleep disorder, sleep disorder using an ECG signal and also a PPG signal if the individual has sleep disorder (sleep apnea).

Table- 1: ECG signal measurements for non-sleep apnea HRV.

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

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

Table 2:- ECG signal measurements for sleep apnea HRV.

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

Table 2 reflects measurements of sleep apnea HRV by taking the ECG signal as input information and comparing the global and local return map.

Table 3:- :- PPG signal measurements for sleep apnea HRV

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

Table 3 reflects measurements of sleep apnea HRV by taking PPG signal as input information and comparing the global and local return map.

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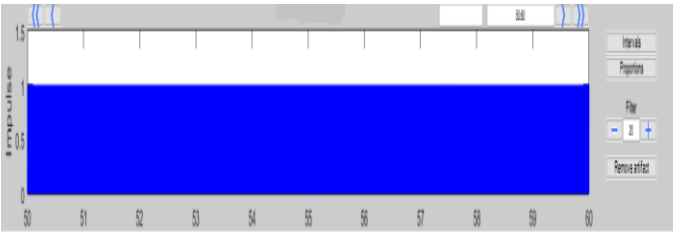

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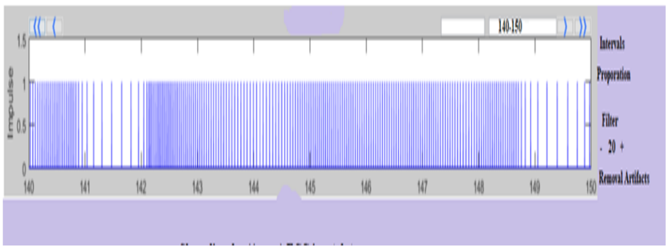

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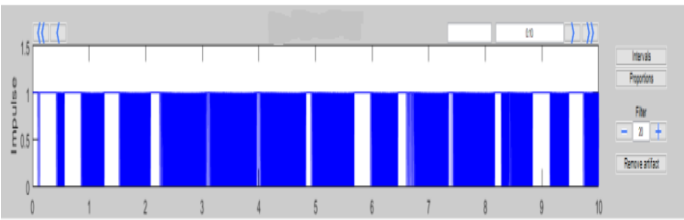
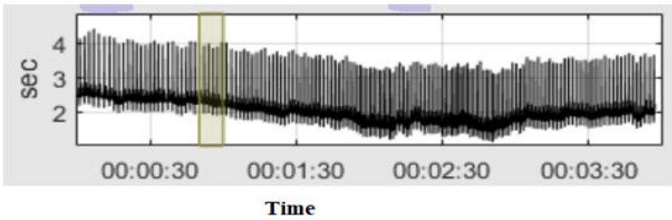


Figure.3. Illustration input data of person. (a) ECG input information for breathing waveforms of non-sleep apnea constitute zero changes. (b) The ECG input information for sleep disorder reflects changes at certain sleep length. (c) PPG input information for sleep apnea reflects fluctuation at some stage of sleep length.

(a)



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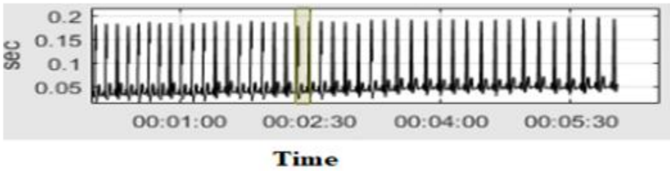

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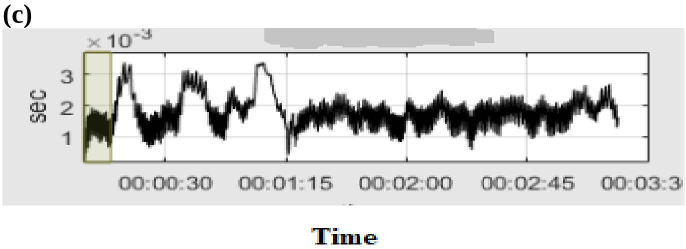
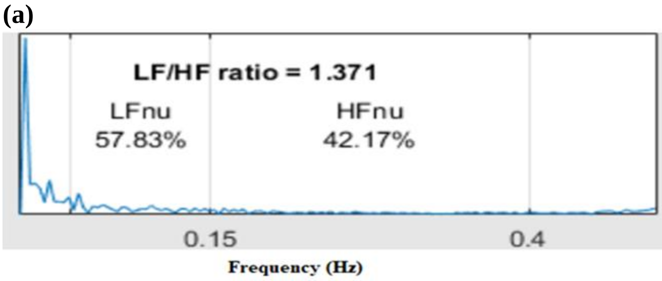


Figure-4: Illustration the RR tachogram which further encloses the mean RR and HR intervals, low and high frequencies. (a) The RR tachogram for non-sleep apnea has lengthy RR and HR intervals and low and high frequency values are 57.83 and 42.2 percentages respectively. (b) The RR tachogram for sleep apnea discovered that drastically increased in RR interval and reduced in HR interval values and reduced low frequency i.e. 29.42 percentage and improved high frequency i.e. 70.58 percentage. (c) The RR tachogram that is further enclosed by the given PPG signal the mean RR and HR intervals, low and high frequencies for sleep disorder. The RR tachogram for sleep apnea using the PPG signal as input information shows that the RR interval is 2,00 and the HR interval is 3,6173. Similarly smaller and greater frequency values are 64.9 and 35.1 percentage respectively.

(a)



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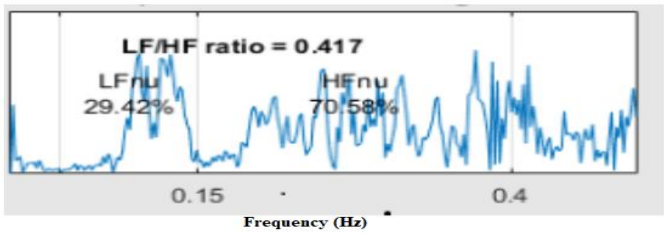

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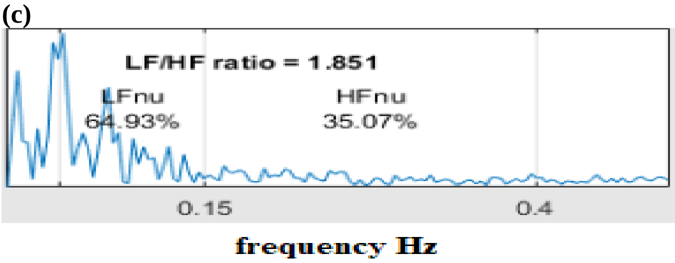
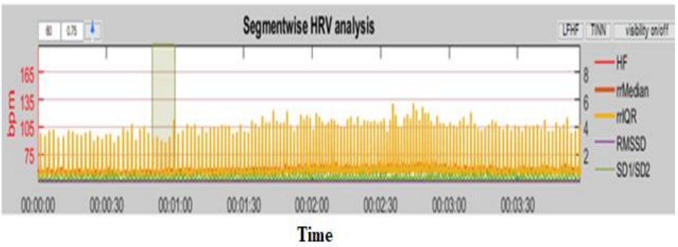


Figure.5: Illustration the spectrum analysis of RR tachogram. (a) RR tachogram spectrum analysis for non-sleep apnea that means the importance of low frequency to high frequency ratios is 1.371. (b) RR tachogram spectrum analysis for sleep apnea that means a value of 0.412 for low frequency to high frequency ratios. (c) PPG signal spectrum analysis of RR tachogram for sleep apnea as input that means low and high frequency ratio value is 1.85.

(a)



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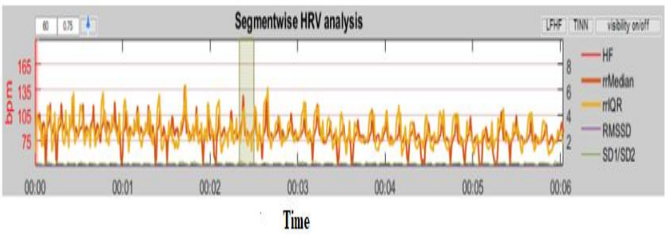

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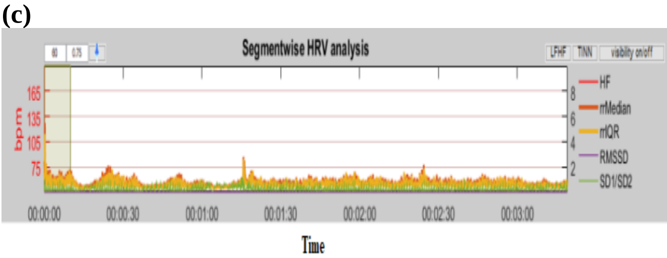

Figure-6: Illustration segmented HRV analysis. (a) ECG signals segmented HRV assessment for non-sleep apnea in which TINN is 16 (b) ECG signal segmented sleep apnea HRV assessment in which TINN is 47. (c) PPG signal segmented sleep apnea HRV assessment in which TINN is 16.

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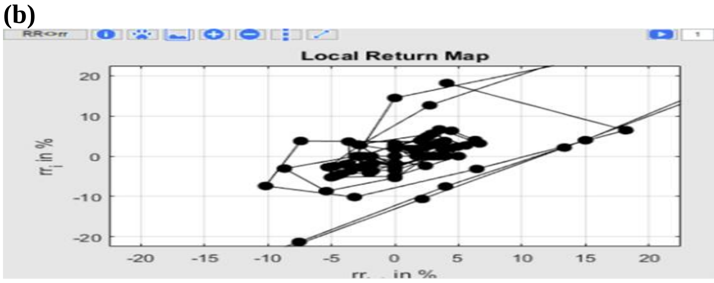
(a)

(b)



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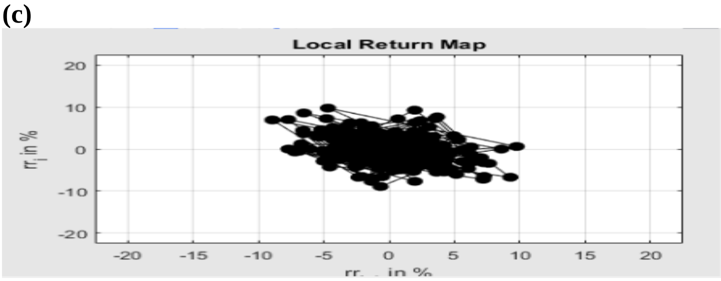
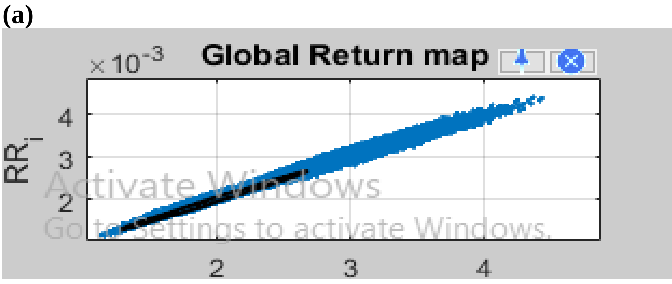


Figure-7: Displays local return maps. (a) Local return generates data about the projections of each RR interval for non-sleep apnea in which the variances of the heart rate is 0.75 and the nodes are nearer. (b) Local return provides data predictions of each RR interval for sleep apnea with a heart r ate variability of 2.83 and farer nodes. (c) Local maps of PPG displays provide data on the predictors of each RR interval for sleep disorder nodes, as well as variability of heart rate is 1.13.

(a)



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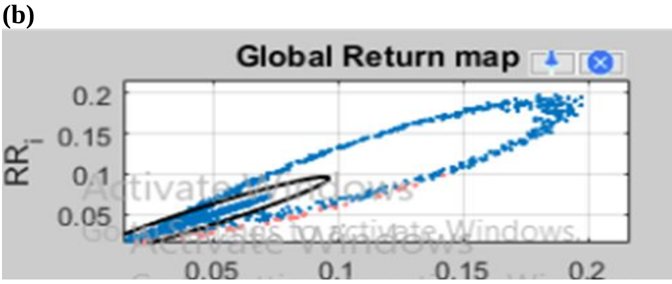

(c)

Figure.8. Displays Poin care plot of global map. (a) Poincare plot generates data of all non-sleep apnea RR intervals with a heart rate variability of 0.90. (b) Poincare plot generates data about whole RR intervals for sleep apnea with variation in heart rate of 2.56. (c) Displays PPG signal imputed poin care plot global map generates data about the entire sleep disorder RR interval in which the heart rate variability is 0.81.

V. CONCULSION

The proposed work creates an algorithm that shows short term event extraction from the ECG signal and combines neural network methodology for the automatic identification of sleep apnea. This analysis can evaluate whether or not the individual has sleep apnea. If the individual does not have sleep apnea, there is no need for further diagnosis. If the individual is suffering from sleep apnea the further diagnosis is made using PPG signal to validate. The proposed work provides subjective data that helps the Doctor find out whether or not the individual is suffering from sleep apnea.

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AUTHORS PROFILE

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