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Sleep Apnea Detection using Cardioid Based Graph

Siti Nurfarah Ain Mohd Azam, Khairul Azami Sidek and Nur Izzati Zainal

Department of Electrical and Computer Engineering,
International Islamic University Malaysia
P. O. Box 10, Jalan Gombak, 50728 Kuala Lumpur
E-mail: azami@iium.edu.my

Abstract

In this study, the development of Cardioid based graph electrocardiogram heart abnormalities classification technique is presented. ECG signals in this work were attained from a public online database UCD Sleep Apnea database (UCDB) with sampling rate of 250 Hz. Each recording has 60 seconds of electrocardiogram signals. Unique features were extracted using the Pan Tompkins algorithm, later Cardioid based graph was formed as the result of the differentiation process. The various shapes of closed-loop created were then observed. From the Cardioid loop, we evaluated the area and standard deviation to differentiate between normal and abnormal heartbeats. As a result, the area, standard deviation, and mean values of abnormal heartbeat were twice the value of a normal heartbeat thus indicating the differences between two types of heart morphologies. Thus, the output of the study suggests the proof-of-concept of our proposed mechanisms to detect heart abnormalities and has the potential to act as an alternative to the current techniques.

Keywords*: ECG signal, Cardioid, Bayes Network, Pan Tompkins, cardiac abnormalities, sleep apnea*

1. Introduction

Sleep apnea is considered as potentially serious disorder and illness in which according to the study conducted by National Sleep Foundation, sleep apnea has affected more than 18 million Americans [1]. Based on the study by the Ministry of Health Malaysia, sleep apnea could influence anybody at any stage of age, including children. In children, sleep apnea is likely to occur due to large tonsils or adenoids. One study completed at Hospital Kuala Terengganu demonstrated that 14.5% of the children there wheezed the first sign that one is a potential sleep apnea sufferer.

Sleep apnea is seen more commonly occurred among men than among women. Left untreated, sleep apnea can have serious life-shortening consequence such as high blood pressure, heart disease, and with the possibility of having stroke. Sleep apnea is caused by the reduction of oxygen in blood due to blocked airway while sleeping as shown in Figure 1.

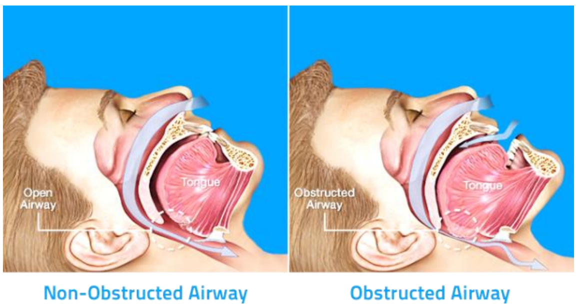

Figure 1. (a) Normal Air Flow While Sleeping, (b) Interrupted Air Flow While Sleeping [11]

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Sleep disturbances and frequent reductions in blood oxygen levels result in excessive daytime sleepiness, lack quality of life, and impaired cognitive function such as memory loss and poor concentration. Risk factors include obesity, smoking, drinking, use of sedatives or tranquilizers, and family history.

Apnea is adapted from the Greek word which means without breath and sleep apnea is referring to the pauses occurs in breathing during the duration of sleep. The major indication of sleep apnea is tremendously loud snoring. Besides that, common sleep apnea symptoms include waking up with a very sore or dry throat, irregularly waking up with a choking or gasping sensation, sleepiness or lack of energy during the day, sleepiness during driving, headaches at the morning, forgetfulness, changes in mood, lessened attentiveness in sex and frequent awakenings or insomnia [2].Treatments usually determined by the severity of each individual instance, and the type of apnea that person suffered with.

In Figure 2 shows the ECG wave for the heart conditions of a person who suffers from sleep apnea. As can be observed, the ECG signal of a normal and healthy person is not the same with an ECG pattern of a person that with heart abnormality.

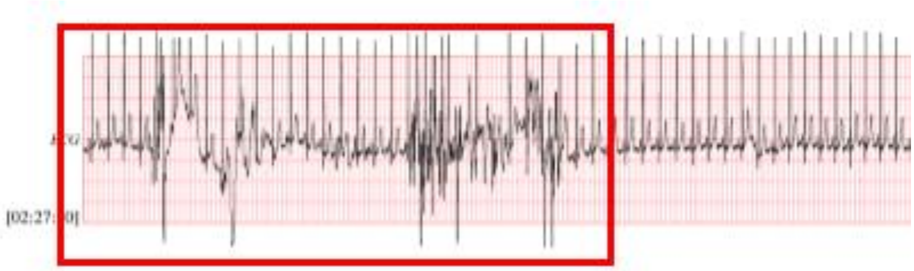

Figure 2. ECG Signals for a Person with Sleep Apnea

From Figure 2, the inconsistencies between a normal and abnormal ECG waveforms is obvious where a normal heart gives a constant shape of ECG wave whereas an abnormal heart has different amplitude reading at certain levels. Due to the differences, this study suggests a simpler and competent technique to identify and categorize heart irregularities by implementing Cardioid based graph technique.

The remaining sections in this paper are structured as follows; the next section will review the related works on heart abnormalities classification technique. Later, Section III, elaborates more on the technique of the study comprises of the data collection procedure, pre-processing, feature extraction and the classification mechanism. After that, in Section IV, the performance of our proposed system is discussed. Last but not least, in Section V, the study is concluded based on the experimentation and results in the previous section.

2. Related Works

In the past decades, there exists a variety of methods introduced to determine the heart's activity. The most widely used technique is analyzing the ECG signal by using Holter monitoring sheets. From the ECG recordings, a medical practitioner is able to identify abnormalities occurred in the heart. In this study, we divide the related literature into two categories; i) non-cardioid method and ii) cardioid-method. These methods will be briefly explained sequentially.

Wang *et al.* in [3] represents the outline and acknowledgment of a compelling sleep stage portrayal method for patients with sleep apnea. The method involves a sequential forward selection (SFS) highlight decision strategy and a decision-tree-based support vector machines (DTB-SVM) classifier for differentiating three sorts of sleep in perspective of ECG signals. At regular time intervals of ECG signal information assembled in the midst of sleep was used to make 24 highlights utilizing heart rate variability (HRV) investigation. A SFS highlight determination strategy was then used to enhance order precision. A DTB-SVM was then prepared by utilizing the data includes as a piece of solicitation to segregate three sleep stages, including pre-sleep mindfulness, NREM sleep and REM sleep. The precicion of the proposed method was 73.51 %.

Other than that, Mendez *et al*. in [4] also proposes a choice appraisal of OSA taking into record ECG signal during sleep time which because of respiratory aggravation creates a particular example on ECG. Mining of ECG qualities, as Heart Rate Variability (HRV) and peak R region, bids choice measures for a sleep apnea pre-detection. 50 recordings originating from the apnea Physionet databank were used as a piece of the examination. A bivariate autoregressive model was applied to survey beat-by-beat force spectral thickness of HRV and R peak zone. k-Nearest Neighbor (kNN) supervised learning algorithms was used for classifying apnea events from ordinary ones, on a minute-by-minute premise for each data. Information was part into two groups, preparing and testing set, every information with 25 recordings. The portrayal results indicated a precision higher than 85% in both training and testing sets.

As explained from the previous section, sleep apnea is the occasion when one either has stops of breathing in, or has low in breath during sleeping. This delay in breathing can go in recurrence and span. Obstructive sleep apnea (OSA) is the normal manifestation of sleep apnea, which is presently tried through polysomnography (PSG) at sleep labs. PSG is both lavish and badly arranged as a specialist human eyewitness is obliged to work over night. Almazaydeh *et al*. in [5] proposed a mechanized characterization calculation which procedures brief time ages of the ECG information. The exhibited arrangement procedure is taking into account support vector machines (SVM) and has been prepared and tried on sleep apnea data from subjects with and without OSA. The outcomes demonstrate that our computerized grouping framework can perceive ages of sleep issue with a high precision of 96.5% or higher.

These are among the research studies performed in the past using non-cardioid techniques. However, identifying heart abnormalities by using the technique of Cardioid based graph for ECG biometric is recognized as a faster and more convenience method as compared to ECG recordings from the Holter readings [6, 7]. There are previous works on Cardioid based graph have been proposed and will briefly discuss about these approaches.

In Sidek *et al*. [6], an analytical approach was applied in order to gain the QRS complex as this portion of the ECG waves is mostly affected by cardiac irregularities. These QRS complexes were used to form the Cardioid based graph by using the differentiated ECG signals. Due to this procedure, the time series representation will be lost and being replaced by set of points. These points are important to determine the centroid (centre coordinate) and the extrema points (distance from the centroid to a certain point). By using this information, the Euclidean distances are calculated. Then MLP was used to categorize the individuals with early and severe Cardiac Autonomic Neuropathy (CAN) obtaining an average classification accuracy of early and severe CAN patients of 99.6% and 99.1%.

In another paper, Sidek et. al. agreed that the demand for a faster diagnosis system is crucial due to CVD mortalities. Thus, related works in [7,8] emphasized that Cardioid is one of the most effective technique to reduce the delay in monitoring CVD patients. ECG recordings were collected from online public databases. The Cardioid based graph was created using the same method in [6]. As classification technique, Bayes Network was implemented in data analysis and pattern recognition with an average classification of 98.4%.

However, based on our knowledge, the previous works were incapable of identifying heart diseases using Cardioid based graph technique. The function of this approach is to identify individual can be further expanded in the domain of classifying heart diseases due to the consistency of abnormal heart morphology and visible abnormal cardiac irregularities detection using Cardioid based graph method. Thus, in this study, we will propose of using Cardioid based graph to detect and identify heart abnormalities.

3. Methodology

Figure 3 summarizes the proposed identification system which consists of the Data Collection, Pre-processing, Feature Extraction and Classification stages. Each stage will be elaborated further in the next sub-sections.

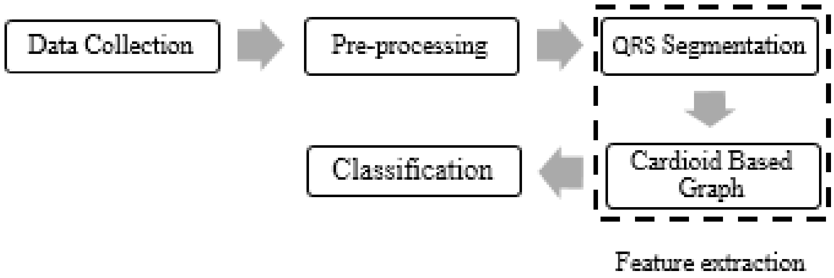

Figure 3. The Proposed Identification System

3.1. Data Collection

A total of 10 ECG signals in for this study were acquired from a public online database called PhysioNet. The data were taken from UCD Sleep Apnea database (UCDB) with sampling rate of 250 Hz. Each recording has 60 seconds of ECG signals.

3.2. Pre-processing

The purpose of pre-processing stage is the removal of high frequency noise and disturbance such as baseline wanderings, muscle noise, *etc*. Besides that, it is also to improve the accuracy of the quality of ECG signals. During this stage, the signals are filtered by using low pass filter. This technique is used to separate the ECG waveform from different noises and to ensure other interfering signals are inactive.

3.3. Feature Extraction

This stage is divided into two main steps which are QRS segmentation and Cardioid based graph.

3.3.1. QRS Segmentation

The QRS waveform is segmented using Pan Tompkins algorithm. As can be observed from Figure 4, the R wave depicts the highest peak in the ECG signals as a result from the activity of the ventricular. The main factor QRS segment was chosen in our analysis because it is fewer affected by heart irregularities, noise and artifacts as shown in aforementioned works as in [8].

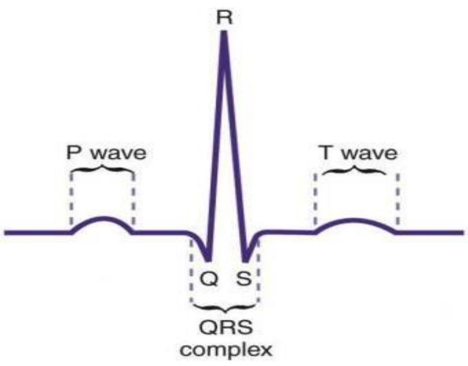

Figure 4. A Typical ECG Signal [9]

3.3.2. Cardioid Based Graph

After obtaining the QRS segments, the Cardioid based graph is created. This step is very important in order to ensure the accuracy of the classification by using this technique. The ECG signal can be represented by $x(t)$ as in Equation 1.

$$\mathbf{x}(t) = \{x(1), x(2), x(3), \ldots, x(N)\} \tag{1}$$

where, x(t) = ECG waveforms and,
N = the total number of QRS complexes for a given period

The QRS waveforms are then differentiated as in Equation 2 in order to acquire the points to form the Cardioid.

$$y(t) = x(n) - x(n-1) \tag{2}$$

where, t = 1, 2, 3. . . (N − 1) and,
$\boldsymbol{y}(t)$ = The differentiated ECG dataset.

A closed loop graph is then plotted based on a scattered XY graph after acquiring the vectors of x and y. The amplitudes of the QRS signals from the ECG are the x-axis and the differentiated ECG values of x are the y-axis. The time series representation is lost once the Cardioid has been plotted and closed loop are shaped as shown in Figure 5. and then the time series ECG signals is converted to a two dimensional loop and from the closed loop pattern, new features are extracted which are the centre coordinate of the graph called centroid and the distance of the centroid to a given point on the cardioid called extrema points.

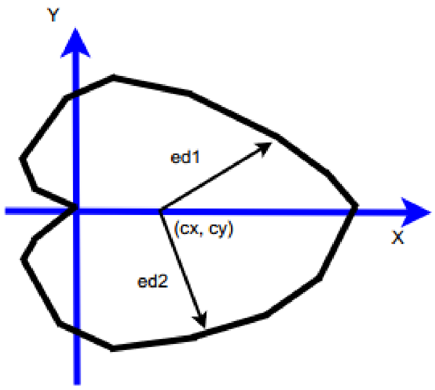

Figure 5. Cardioid Based Graph for Normal Heartbeat [6]

Centroid of the Cardioid graph is attained by implementing Equation 3 and it is signified as *cx* and *cy*.

$$(cx, cy) = \left[\frac{\sum_{i=1}^{N} x(i)}{N}, \frac{\sum_{i=1}^{N} y(i)}{N}\right] \tag{3}$$

where cx and cy are the position of the coordinate of the centroid in the Cardioid graph. Using the centroid, the Euclidean distances, *ed(i)* are then calculated by using Equation 4.

$$ed(i) = \sqrt{(cy - y(i))^2 + (cx - x(i))^2} \tag{4}$$

3.4. Classification

For classification of the proposed system, a statistical approach is implemented. The results are evaluated by using three parameters which are area, standard deviation and mean. The area of the Cardioid is obtained by applying the formula of a polygon. The standard deviation is then derived after calculating the area of the Cardioid. Both calculations are executed by using MATLAB. The purpose of this approach is to validate the accuracy of the propose technique by determining the differences between normal and abnormal heartbeats.

4. Experimentation and Results

In this section, the experimentation and result using the proposed identification system as shown in Figure 3 is described in detail. To briefly recap, the stages involved are Data Collection, Pre-processing, Feature Extraction and Classification stages.

Figure 6 shows the raw ECG signals of subject *ucddb021_recm* sleep apnea patient as an example of the Data Collection stage.

The ECG signal is then filtered by using derivative filter as presented in Figure 7. The purpose of filtering is to remove the unwanted noise such as baseline wandering produced from the movement of the body. Besides that, it is also to boost the accurateness of the quality of ECG signals. This step justifies the second phase which is Pre-processing.

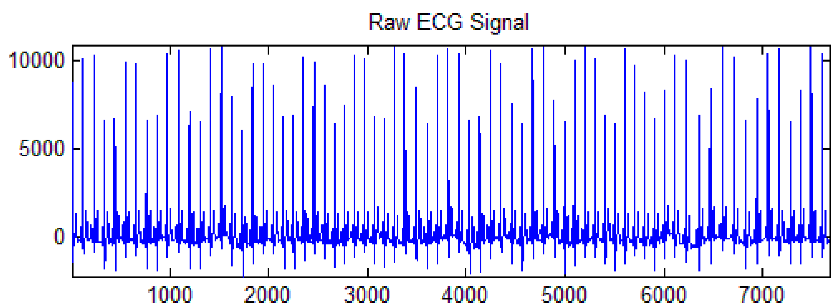

Figure 6. Raw ECG Signal of subject ucddb021_recm with Sleep Apnea

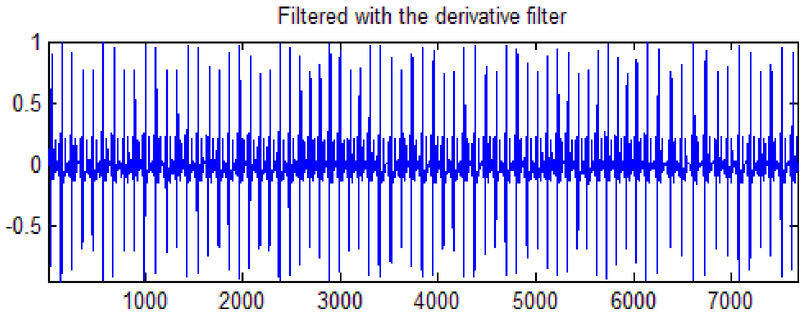

Figure 7. ECG Signal After Filtering Using Derivative Filter

Then, Pan Tompkins algorithm was applied in order to perform segmentation of the QRS complexes after filtering process as shown in Figure 8. This is the first part of the Feature Extraction stage whereas the second part involves the formation of the Cardioid graph.

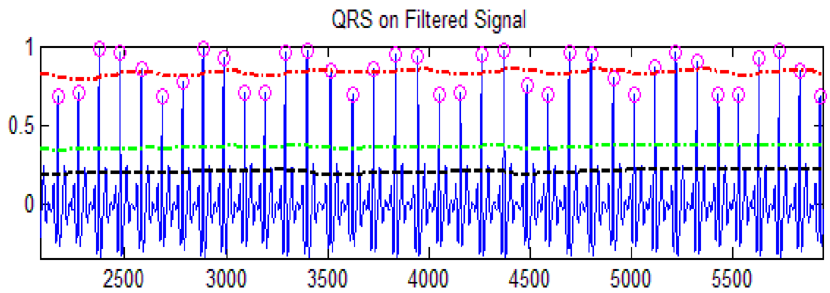

Figure 8. QRS Segmentation of ECG Filtered Signal

After the amputation of the noise and segmentation, a Cardioid graph is formed as illustrated in Figure 9. In order to produce the Cardioid graph, the R peak points are identified, and the coordinates from Q to S waves are taken.

As can be observed from the figure, the contour of the graph is inconsistent where some are small and some are big. This is due to the occurrence of normal and abnormal heartbeats. The purpose of this stage is to compute the dissimilarities between normal and abnormal heartbeat. The looping of the graph for the normal ECG is consistent in shape as can be observed from the figure. The graph that is formed outside the constant shaped loop indicates the abnormal heart beat which indicates the occurrence of sleep apnea.

Two segmented QRS were taken for normal heartbeat and another two segmented QRS for abnormal heartbeat. Then, the Cardioid graph is formed to calculate its area and the standard deviation.

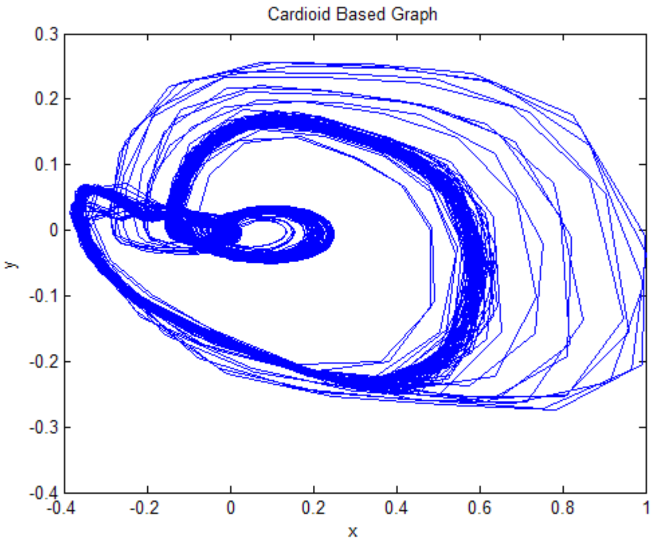

Figure 9. Cardioid Based Graph of Sleep Apnea Patient

The results from the segmented ECG signals of normal and abnormal heartbeat shows the area of the abnormal ECG signals is larger than the normal signals. The value of the standard deviation also differs where the abnormal ECG signals are twice higher than the value of standard deviation of the normal ECG signals.

In order to confirm the result, the Cardioid graph was plotted. From Figure 10, the red lines indicate the occurrence of sleep apnea and the blue line shows the normal heartbeat.

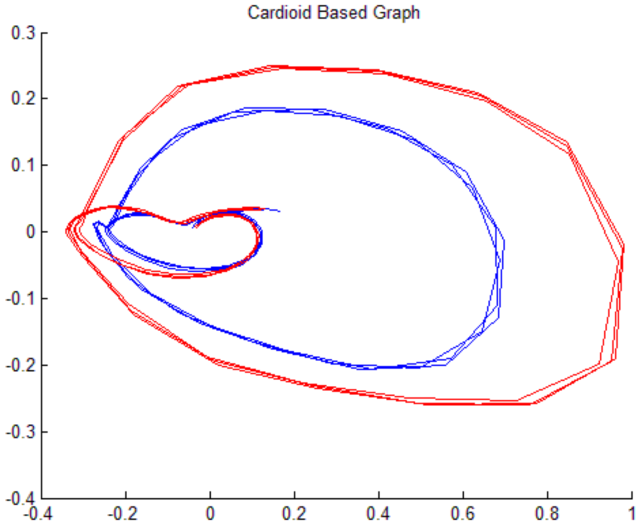

Figure 10. Cardioid Based Graph of Segmented ECG signals

Tables 1, 2 and 3 reflect the results of the area, the standard deviation and mean of Cardioid based graph for the entire subject tested. As can be observed, the values of the area for normal are smaller than the abnormal heartbeat. Similarly, the same results are true for standard deviation. The values for normal heartbeat are smaller as compared to the abnormal heartbeat. While sleeping, minimal activity occurs this causes the heartbeat to remain calm. However, when the sleep apnea occurs, the heartbeat amplitude experiences a sudden increase which leads to bigger Cardioid graphs. Thus, the value of the area and its standard deviation will be higher.

Table 1. Area of the Cardioid Based Graph

Subject	Normal 1	Normal 2	Normal 3	Abnormal 1	Abnormal 2	Abnormal 3
ucdbb002_recm	0.3340	0.3373	0.3109	0.5375	0.5002	0.5017
ucddb003_recm	0.4097	0.4205	0.4307	0.5431	0.5299	0.5122
ucddb006_recm	0.1992	0.2139	0.2012	0.5658	0.5530	0.5444
ucddb007_recm	0.2415	0.2347	0.2332	0.4743	0.4926	0.5108
ucddb009_recm	0.3861	0.3966	0.3855	0.5375	0.5376	0.5675
ucddb011_recm	0.3397	0.3386	0.3579	0.5256	0.5552	0.5090
ucddb013_recm	0.3887	0.4279	0.3965	0.5569	0.5718	0.5358
ucddb014_recm	0.3668	0.4293	0.5385	0.5918	0.6380	0.5729
ucddb018_recm	0.2447	0.2560	0.2887	0.5328	0.5446	0.5478
ucddb021_recm	0.2921	0.2938	0.3055	0.5233	0.5399	0.5499

Table 2. Standard Deviation of the Cardioid Based Graph

Subject	Normal 1	Normal 2	Normal 2	Abnormal 1	Abnormal 2	Abnormal 3
ucdbb002_recm	x = 0.2397 y = 0.0771	x = 0.2472 y = 0.774	x = 0.2319 y = 0.0744	x = 0.3090 y = 0.0978	x = 0.2994 y = 0.0943	x = 0.2968 y = 0.0945
ucddb003_recm	x = 0.2660 y = 0.0855	x = 0.2682 y = 0.0867	x = 0.2700 y = 0.0877	x = 0.3053 y = 0.0986	x = 0.3053 y = 0.0973	x = 0.2942 y = 0.0957
ucddb006_recm	x = 0.1626 y = 0.0458	x = 0.1678 y = 0.0475	x = 0.1625 y = 0.0461	x = 0.2746 y = 0.0768	x = 0.2677 y = 0.0760	x = 0.2686 y = 0.0754
ucddb007_recm	x = 0.1964 y = 0.0658	x = 0.1954 y = 0.0650	x = 0.1931 y = 0.0648	x = 0.2916 y = 0.0921	x = 0.2959 y = 0.0938	x = 0.3022 y = 0.0956
ucddb009_recm	x = 0.2286 y = 0.0768	x = 0.2248 y = 0.0779	x = 0.2254 y = 0.0769	x = 0.2740 y = 0.0905	x = 0.2819 y = 0.0930	x = 0.2749 y = 0.0905
ucddb011_recm	x = 0.2378 y = 0.0783	x = 0.2369 y = 0.0781	x = 0.2394 y = 0.0803	x = 0.3073 y = 0.0968	x = 0.3176 y = 0.0995	x = 0.3046 y = 0.0952
ucddb013_recm	x = 0.2586 y = 0.0835	x = 0.2721 y = 0.0874	x = 0.2598 y = 0.0841	x = 0.3100 y = 0.0996	x = 0.3156 y = 0.1009	x = 0.3051 y = 0.0977
ucddb011_recm	x = 0.2445 y = 0.0823	x = 0.2527 y = 0.0882	x = 0.2918 y = 0.0990	x = 0.3106 y = 0.1033	x = 0.3300 y = 0.1065	x = 0.3006 y = 0.1019
ucddb018_recm	x = 0.2238 y = 0.0657	x = 0.2300 y = 0.0672	x = 0.2431 y = 0.0716	x = 0.3230 y = 0.0970	x = 0.3254 y = 0.0983	x = 0.3278 y = 0.0983
ucddb021_recm	x = 0.2308 y = 0.0724	x = 0.2326 y = 0.0726	x = 0.2348 y = 0.0739	x = 0.3139 y = 0.0966	x = 0.3184 y = 0.0981	x = 0.3208 y = 0.0990

Table 3. Mean of the Cardioid Based Graph

Subject	Area (Normal)	Area (Abnormal)	Standard Deviation (Normal)	Standard Deviation (Abnormal)
ucdbb002_recm	0.3274	0.5132	x = 0.2396, y = 0.0763	x = 0.3017, y = 0.0955
ucddb003_recm	0.4203	0.5284	x = 0.2681, y = 0.0866	x = 0.3000, y = 0.0972
ucddb006_recm	0.2048	0.5544	x = 0.1643, y = 0.0465	x = 0.2703, y = 0.0761

ucddb007_recm	0.2365	0.4926	x = 0.1950, y = 0.0652	x = 0.2966, y = 0.0938
ucddb009_recm	0.3894	0.5475	x = 0.2275, y = 0.0772	x = 0.2769, y = 0.0913
ucddb011_recm	0.3454	0.5299	x = 0.2380, y = 0.0789	x = 0.3099, y = 0.0972
ucddb013_recm	0.4043	0.5548	x = 0.2635, y = 0.5548	x = 0.3102, y = 0.0994
ucddb014_recm	0.4449	0.05989	x = 0.2630, y = 0.0899	x = 0.3137, y = 0.1039
ucddb018_recm	0.2631	0.5417	x = 0.2323, y = 0.0682	x = 0.3254, y = 0.0979
ucddb021_recm	0.2971	0.5377	x = 0.2327, y = 0.0730	x = 0.3177, y = 0.0979

5. Conclusion

To conclude, in this study, we have demonstrated an efficient and accurate Cardioid based graph ECG heart abnormality classification technique for sleep apnea patients using statistical methods and a classification algorithm. In the statistical approach, the area and standard deviation values of abnormal heartbeat double the value of a normal heartbeat. All of these statistical parameters indicate the reliability of the proposed system to classify the heart abnormality for sleep apnea. Furthermore, the classification outcomes approach suggests that the proposed method gives important heart abnormality detection with a classification accuracy of as low as 12.5%. Therefore, this output indicates that Cardioid based graph ECG heart abnormality classification technique has the ability to differentiate between normal and abnormal heartbeat as an alternative to the current techniques.

References

[1] American Sleep Apnea Association, Sleep Apnea, **(2015)**, http://www.sleepapnea.org/learn/sleep-apnea.html
[2] W. Blahd, Sleep Apnea Symptoms, **(2015)**, http://www.webmd.com/sleep-disorders/sleep-apnea/symptoms-of-sleep-apnea
[3] J. S. Wan, G. R. Shih and W. C. Chiang "Sleep stage classification of sleep apnea patients using decision-tree-based support vector machines based on ECG parameters", Biomedical and Health Informatics (BHI), 2012 IEEE-EMBS International Conference, **(2012)**, pp. 285-288.
[4] M. O. Mendez, D. D. Ruini, O. P. Villantieri, M. Matteucci, T. Penzel, S. Cerutti and A. M. Bianchi, "Detection of Sleep Apnea from surface ECG based on features extracted by an Autoregressive Model", Engineering in Medicine and Biology Society, 2007, EMBS 2007, 29th Annual International Conference of the IEEE, **(2007)**, pp.6105-6108.
[5] L. Almazaydeh, K. Elleithy and M. Faezipour, "Obstructive sleep apnea detection using SVM-based classification of ECG signal features", Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, **(2012)**, pp. 4938-4941.
[6] K. A. Sidek, H. F. Jelinek and I. Khalil, "Identification of Cardiac Autonomic Neuropathy patients using Cardioid based graph for ECG biometric", Computing in Cardiology, **(2011)**, pp. 517-520.
[7] F. K. Sufi and Z. I. Tari, "A Cardiod based technique to identify Cardiovascular Diseases using mobile phones and body sensors", Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE, **(2010)**, pp. 5500-5503.
[8] F. Sufi, I. Khalil and I. Habib, "Cardioids-based faster authentication and diagnosis of remote cardiovascular patients", Security Comm. Networks, vol. 4, **(2011)**, pp. 1351–1368.
[9] K. Sidek and I. Khali, "Biometric sample extraction using Mahalanobis distance in Cardioid based graph using electrocardiogram signals", Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, **(2012)**, pp.3396-3399.
[10] K. A. Sidek, H. F. Jelinek and I. Khalil, "Identification of Cardiac Autonomic Neuropathy patients using Cardioid based graph for ECG biometric", Computing in Cardiology, **(2011)**, pp.517-520.
[11] What exactly is sleep apnea?, **(2015)**, http://www.drbraegger.com/sleep-apnea/

