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Sleep Apnea Diagnosis by DWT-Based Kurtosis, Radar and Histogram Analysis of Electrocardiogram

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ABSTRACT
Sleep Apnea is a serious breathing disorder that occurs when a person's breathing is interrupted during sleeping. People with sleep Apnea stop breathing repeatedly during their sleep, which means that the brain and rest of the body may not get enough oxygen. If left untreated, sleep Apnea can result in a number of health problems, including high blood pressure, stroke, heart failure, irregular heartbeats, heart attacks, and depression. This paper deals with sleep Apnea assessment by discrete wavelet-transformation-(DWT)-based kurtosis, radar and histogram analysis of electrocardiogram (ECG) signals. ECG signals are de-noised by passing them through well-known Savitzky–Golay FIR filter and then are decomposed at different DWT levels, and kurtosis of approximate and detailed coefficients at different DWT levels is measured. Kurtosis at different levels is compared for a healthy person and Apnea patients. Then, radars are formed by kurtosis and compared. Histogram analysis is done on both ECG signals and obtained kurtosis. The comparative study shows that up to DWT level-4, kurtosis of approximate coefficients of Apnea patients is lower than that of a healthy person. However, kurtosis of the approximate coefficient for Apnea patients is greater than that of a normal person at DWT level-7. Up to level 6, Kurtosis of detailed coefficients for Apnea patients is less than that of a normal person. Radar shapes and histogram peaks of ECG signal and kurtosis are also different between a normal person and Apnea patients. Probability in terms of a "p" value for Kurtosis at optimized DWT levels for Apnea patients has shown satisfactory outcome.

KEYWORDS
Discrete wavelet transform; Detailed and approximate coefficient; Electrocardiogram; Histogram; Kurtosis; Radar; Sleep Apnea

1. INTRODUCTION

For heart disease diagnosis, electrocardiogram (ECG) has become the most useful signal and research on electrocardiogram signals is going on for long. ECG analysis [1] has also been done for human identification. Different decomposition and data compression techniques have been introduced [2–4]. Singular value decomposition technique has been used for ECG extraction in [2]. Data compressed sensing technology with wireless ECG systems [3], a real-time energy-efficient ECG-Compression technique [4] and a new compression algorithm [5] have been developed. Beat-to-beat observation of ECG signals are very important. Mathematical tools for assessment of beat-to-beat variations in ECG signals [6] have been introduced. Histogram analysis of Periodic ECG artifacts in EEG is done [7]. Data security for ECG transmission is presented in [8]. Different digital ECG formats developed have been developed for analysis [9]. Low-power portable system [10], mobile trans-telephonic system [11], underwater ECG monitoring system [12], flexible dry electrodes [13] and bluetooth technology [14] have been developed for ECG monitoring. Different heart diseases have been diagnosed with ECG monitoring. Cardiac Ischemia has been detected by Spatio-temporal Information of Standard ECG Leads [15]. Cardiovascular abnormalities are diagnosed by data-mining-based approach [16]. For better assessment, lossless data compressor by wireless sensors [17] and Adaptive Kalman Filter [18] have been applied in ECG signal assessment. Characterization of ECG has been done by wavelet transforms [19]. A dynamical model [20] has been developed for generating synthetic electrocardiogram signals. Rough Set Decision System has been made to classify different heart diseases [21].

In conventional practice, ECG signal is characterized by its different parts of the shape, namely P wave, PR segment, QRS Complex, ST segment, T wave, U wave, PR interval, and QT interval (Figure A1, Appendix). Based on these parameters, classification and characterization of ECG signals are done. Different new approaches have been introduced for characterization of ECG signals. For example, tree approach using spatio-temporal information [15], data mining approach [16], wavelet-transformation-based approach [19], and fuzzy rough set decision making system [21] have been introduced in recent years for characterization of ECG signals.

As ECG signals are non-stationary in nature, DWT-based assessment has been done [22,23] for ECG monitoring. However, very few of these works relate ECG features with discrete-wavelet-decomposition-based statistical parameter like Kurtosis [22–25] values and radars [26–29], which are now often used in other application of periodic and non-stationary signal assessment. An automated detection mechanism has been introduced for the diagnosis of sleep apnea from electrocardiogram signals using nonlinear parameters [30]. Automated diagnosis of coronary artery disease has been done using tunable-Q wavelet transform applied on heart rate signals [31]. A detailed review of ECG-based diagnosis support systems for obstructive sleep apnea has been presented in [32]. An integrated alcoholic index has been introduced using tunable-Q-wavelet-transform-based feature extracted from EEG signals for diagnosis of alcoholism [33].

Very few attempts have been taken to utilize those approaches for diagnosis of heart diseases. Wavelet-transform-based techniques were found very suitable for assessment of non-stationary signals whose nature may vary with respect to both time and frequency [29]. Nature of non-stationary signals varies with respect to both time and frequency. Fourier transform gives frequency domain information. But wavelet transform gives information in both time and frequency domain, it is suitable for assessment of non-stationary waves. Moreover, the data capturing process used in the present-day technology is digital in nature, which capture continuous signal in a discrete manner, from where signals are reconstructed for analysis. To deal with non-stationary signal, DWT-based assessment is found very effective. In this work, Apnea disease has been considered and an attempt has been made to distinguish ECG signals of Apnea patient from normal ECG signals based on an assessment of DWT-based kurtosis of approximate and detailed coefficients, Radar & Histogram analysis. The nature of DWT-based Kurtosis and shapes of radars of Kurtosis of Sleep Apnea patients are found different from that of normal ECG signals, which are significant for the study of non-stationary ECG signals and diagnosis of Sleep Apnea. ECG signals having sleep apnea have been classified and differentiated from that of normal persons.

2. DATA ACQUISITION

For ECG analysis, data from well-known resource www.physionet.org [34] have been used. ECG signals under consideration have been collected from normal persons as well as Apnea patients. Each set of data have been taken for 10 seconds with a thousand samples having an interval of 0.1 ms. Data have been captured as voltage signals in terms of mV. Each set of data consists of 10–11 cycles. Collected data are stored in CSV format and used for denoizing and further analysis.

3. DE-NOISING OF ECG SIGNALS

Electrocardiogram signals are collected for normally healthy persons and sleep apnea patients [34]. Signals are then de-noised by passing them through Savitzky–Golay (S–G) FIR filter [35]. Savitzky–Golay smoothing filters are referred to as digital smoothing polynomial filters and least-squares smoothing filters. S–G filters are used to 'smooth out' a noisy signal having a large frequency span without noise. In smoothing application, S–G filters show a much better performance than standard averaging FIR filters for elimination of noise content. These filters are optimal by minimizing the least-squares error in fitting a polynomial to frames of noisy data. Tools available in Matlab (version 15) have been used for this purpose; 'sgolayfilt(x,k,f)' applies to the data in vector matrix x. The polynomial order k is less than the frame size, f, and it must be odd. De-noising up to 15th level is done. After denoizing, Kurtosis, Radar and Histogram analysis are done as shown by the schematic diagram in Figure 1.

4. KURTOSIS ANALYSIS

4.1 Kurtosis

Kurtosis is often applied to verify whether data set is peaked or flat relative to a normal distribution. Data set have a peak or a flat top near the mean if they have high or low kurtosis value respectively. Kurtosis is

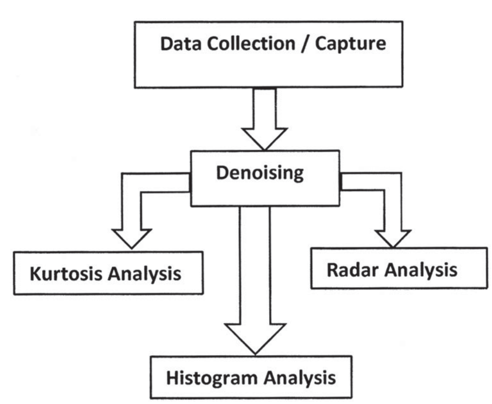

Figure 1: Schematic diagram for apnea assessment

mathematically defined as [29]

$$Kurtosis = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^4}{(n-1)\sigma^4} - 3, \quad (1)$$

where x_i is data, n is a number of data, $\bar{x}$ is mean of data and σ is the standard deviation.

4.2 Kurtosis of ECG Signal for Normal Patient and Apnea Patient

De-noised ECG signals are decomposed at different DWT levels. Then, Kurtosis of approximate and detailed coefficients of ECG signals at different DWT decomposition levels both for a normal person and Apnea patient are measured, as presented in Tables 1 and 2.

4.3 Comparison of Kurtosis

Then, a comparative study of kurtosis of DWT-based approximate and detailed coefficient has been made. Kurtosis values of approximate coefficient of a normal healthy person and an Apnea patient have been shown in Figure 2. It shows that for a normal healthy person, the kurtosis of the approximate coefficient is high and constant in magnitude up to level 4, then decreasing with a negative slope up to level 7, and then gradually decreasing slowly. It is highest at level 1 to 4. For the Apnea patient,

Table 1: Kurtosis of approximate coefficients of ECG signals at different DWT decomposition levels

DWT LEVEL	Kurtosis of approximate coefficients (KA) for a normal person	Kurtosis of approximate coefficients (KA) for an Apnea patient
1	12.44702	2.89829
2	12.44704	2.694871
3	12.43487	2.787467
4	11.84149	2.753931
5	7.991156	2.073999
6	3.538881	2.762352
7	2.89196	3.846504
8	2.164103	3.611258
9	2.271898	2.059815

Table 2: Kurtosis of detailed coefficients of ECG signals at different DWT decomposition levels

DWT LEVEL	Kurtosis of detailed coefficients (KD) for a normal person	Kurtosis of detailed coefficients (KD) for an Apnea patient
1	42.63338	15.09395
2	17.72542	9.326614
3	18.57031	6.325306
4	12.93027	4.622486
5	10.54336	2.550944
6	6.342219	2.098988
7	1.993969	4.604587
8	1.590215	2.165523
9	1.633053	2.350683

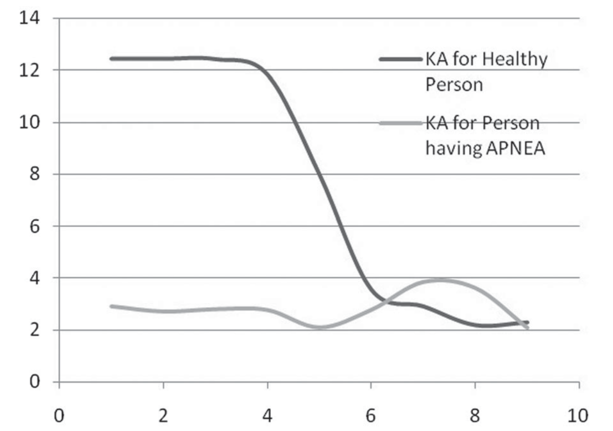

Figure 2: Kurtosis of the approximate coefficient of a normal healthy person and Apnea patient

the kurtosis of the approximate coefficient is comparatively small in magnitude, then increasing with a positive slope up to level 7, and then gradually decreasing. It is highest at level 7.

Kurtosis values of detailed coefficient of normal healthy person and Apnea patient have been shown in Figure 3. In both cases, kurtosis of the detailed coefficient is decreasing with the increase of the level of decomposition. However, the rate of decrease of kurtosis values for apnea patient is slower than that of a normal person. It shows that for a normal healthy person, the kurtosis of the detailed coefficient is high at level 1, then decreasing with a negative slope up to level 7 and then gradually they become constant and almost the same at level 8 and 9. Up to level 6, Kurtosis values of detailed coefficients for Apnea patients are less than that of a normal person. Thus, monitoring the kurtosis nature with respect to different decomposition levels of ECG signals can give an idea about the existence of apnea.

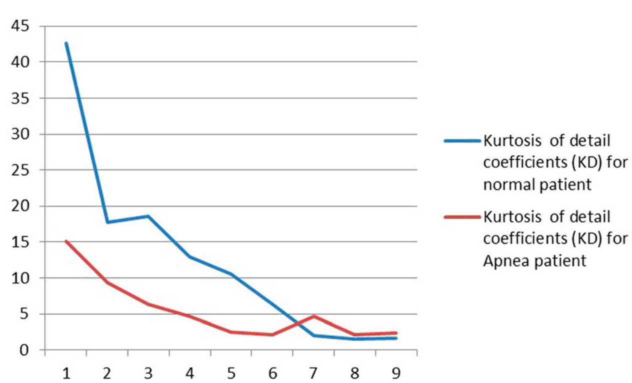

Figure 3: Kurtosis of the detailed coefficient of a normal healthy person and Apnea patient

5. RADAR ANALYSIS

Radar is one sort of popular plot, also known as spider chart, where all samples under consideration are plotted in two dimensional chart; relative position and angle of axes are uniformly distributed in 360°. Radar of Kurtosis of DWT-based approximate coefficients is then formed both for a normal person and Apnea patient, as shown in Figure 4. It shows distinct variations in shape and decrease in the area for Apnea patient, which may be used for easy isolation of Apnea signals from normal signals. Radar corresponding to a healthy person is shown by deeply shaded area and that of apnea patient is shown by lightly shaded area; the area for apnea patient is much less than the area for a normal person.

Radar of Kurtosis of DWT-based detailed coefficients is then formed both for a normal person and Apnea patient, as shown in Figure 5. It shows distinct variations in shape and decrease in the area for Apnea patient, which may be used for easy isolation of Apnea signals from normal signals. In this case also, the area of radar formed by KD of a normal person is higher than that of the apnea patient. Thus, the existence of apnea reduces the area of radar formed by KD-like radar formed by KA. Measurement of areas of different radars may give an index of apnea.

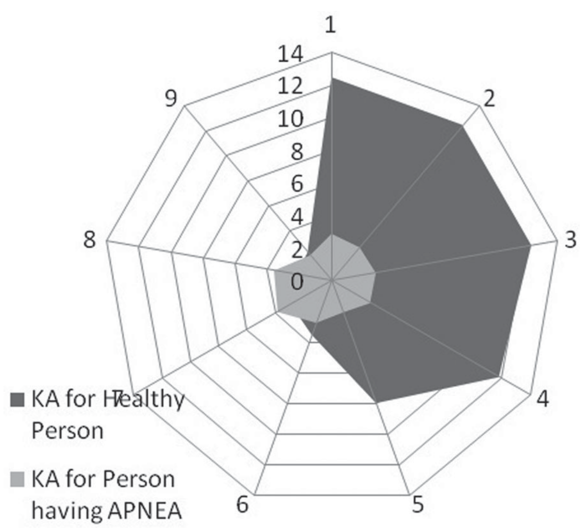

Figure 4: Radar of Kurtosis of DWT-based approximate coefficients of a normal healthy person and Apnea patient

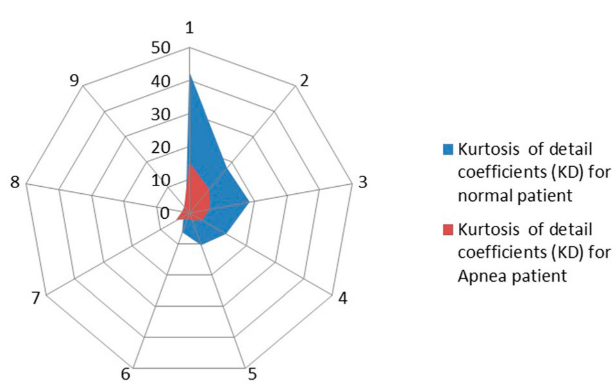

Figure 5: Radar of Kurtosis of DWT-based detailed coefficients of a normal healthy person and Apnea patient

6. HISTOGRAM ANALYSIS

Histogram refers to the distribution of numerical data to estimate the probability distribution of a continuous variable. Unlike bar graph, it deals with only one variable. Histogram Assessment of ECG Signals and Kurtosis of DWT-based approximate coefficients are then formed of the normal person and the Apnea patient, as presented in Figure 6(a) and Figure 6(b), respectively. Peak value in

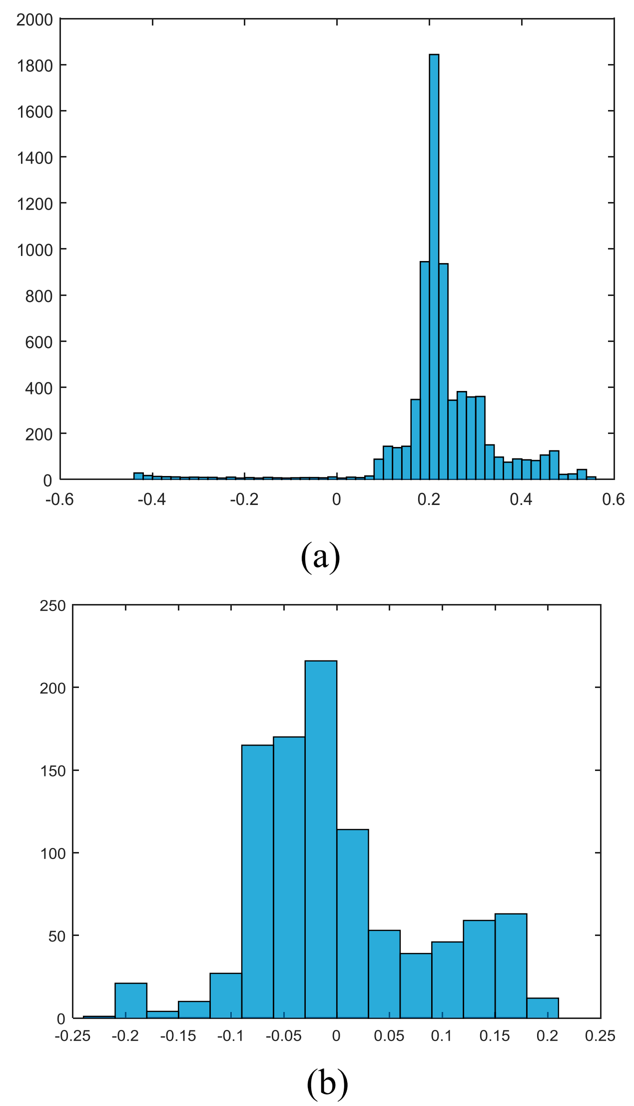

Figure 6: Histogram assessment of ECG signals of (a) a normal healthy person and (b) Apnea patient. (a) Histogram of ECG of a normal healthy person. (b) Histogram of ECG of an Apnea patient

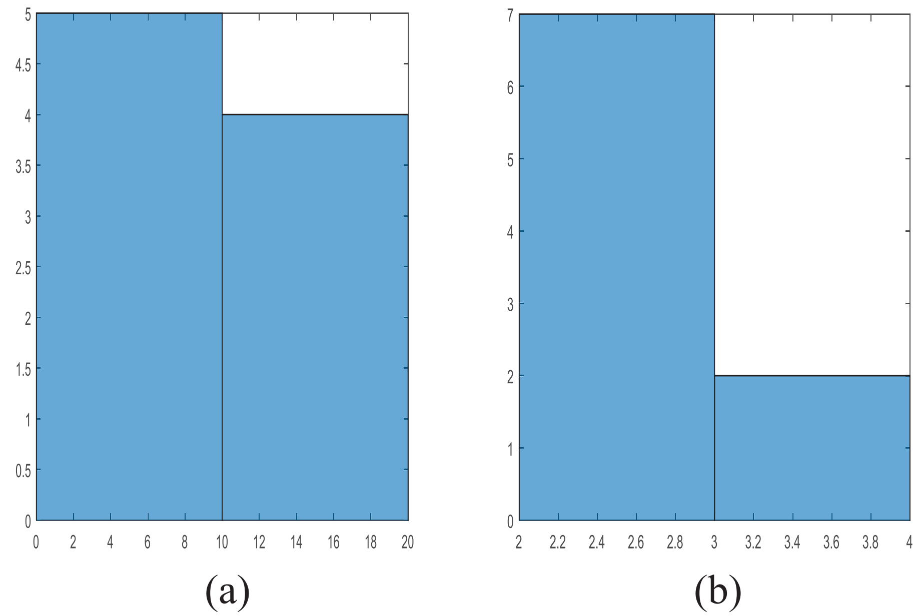

Figure 7: Histogram assessment of DWT-based approximate coefficients of (a) a normal healthy person and (b) Apnea patient

the histogram of the ECG signal shown in Figure 6(a) is higher than that shown in Figure 6(b).

Histogram of kurtosis values for the normal person and the Apnea patient have been formed as shown in Figure 7(a) and Figure 7(b) a respectively. Figure 7 shows that the number of columns of the histogram for kurtosis is much less than that of ECG signals. Peak value of the histogram for kurtosis has increased for the Apnea patient.

7. STATISTICAL DATA VALIDATION

A total of 50 cases have been considered for statistical validation in which 20 cases are done with normal persons and 30 cases are done with Apnea patients. All are in the age group of 40–45 years. 50% cases of normal persons and Apnea patients are taken from the female category. For a male, weights are between 65 and 80 Kg and heights are between 158 and 176 cm. For a female, weights are between 55 and 70 Kg and heights are between 153 and 170 cm. In all cases, radar,

Histogram and Wavelet-decomposition-based Kurtosis analysis shows similar-type features for normal and for sleep Apnea patients. For the apnea patient, the nature of Kurtosis values for approximate and detail coefficients with respect to DWT levels are found similar; the corresponding shape of radars are of the same type. The difference between maximum and minimum of kurtosis value at each DWT level for apnea patients is found less than 5%. DWT-level-wise percentage variation of Kurtosis for detailed and approximate coefficients with respect to maximum Kurtosis values for each DWT level is added in Table 3.

Table 3: Percentage variation of KD and KA coefficients with respect to maximum Kurtosis values for each DWT level

DWT Level	Percentage Difference between maximum and minimum of KA for Apnea Patients $\frac{KA_{max}-KA_{min}}{KA_{max}} \times 100\%$	Percentage Difference between maximum and minimum of KD for Apnea Patients $\frac{KD_{max}-KD_{min}}{KD_{max}} \times 100\%$
1	2.34	2.25
2	2.02	2.00
3	1.45	1.60
4	1.20	1.45
5	0.80	0.95
6	2.53	2.80
7	3.85	3.35
8	4.25	4.10
9	4.20	4.05

Table 4: *p*-Value obtained for optimized KA and D

Parameter under consideration	*p*-Value
KA at DWT level1	.83
KA at DWT level2	.81
KA at DWT level3	.85
KD at DWT level1	.81

A comparative study on kurtosis of approximate coefficient shows that the difference of KA between apnea patient and a normal person is found maximum at DWT levels 1, 2, and 3. A comparative study of Kurtosis of detail coefficient shows that the difference of KD between apnea patient and a normal person is maximum at DWT level 1. The p value of a test refers to probability, under the null hypothesis, of obtaining a value of the test statistic as extreme or more extreme than the value computed from the sample. Based on this observation of KA, a p value of KA has been estimated for DWT levels 1, 2., and 3 for the

Table 5: Features extracted from the statistical analysis

Sl. No	Features extracted from ECG signal of the normal person	Features extracted from ECG signals of Apnea patient
1.	Kurtosis of the approximate coefficient for a normal healthy person is higher than that of an Apnea patient up to level 4	Kurtosis of the approximate coefficient for an apnea patient person is less than that of a normal person up to level 4
2.	At level 7, Kurtosis of the approximate coefficient for a normal healthy person is less than that of an Apnea patient	At level 7, Kurtosis of the approximate coefficient for an apnea patient is higher than that of a normal person
3.	Up to level 6, Kurtosis of detailed coefficients for a normal person is higher than that of an Apnea patient	Up to level 6, Kurtosis of detailed coefficients for Apnea patients is less than that of a normal person
4.	Area of Radar of Kurtosis values for a normal person is much higher than that of an Apnea patient	Area of Radar of Kurtosis values for an Apnea patient is much less than that of a normal person
5.	The peak value of the Histogram of ECG signals for a normal person is higher than that of an Apnea patient	The peak value of Histogram of ECG signals for Apnea patient is less than that of a normal person
6.	The peak of Histogram of kurtosis of the approximate coefficient of a normal person is less than that of an Apnea patient	The peak of Histogram of kurtosis of the approximate coefficient of an Apnea patient is higher than that of a normal person

apnea patient; based on the observation of KD, a p value of KD has been estimated for DWT level 1 for the apnea patient. In all cases, p value has been found greater than 0.8, as presented in Table 4.

8. COMPARATIVE STUDY AND SPECIFIC OUTCOME

A comparative study shows that Kurtosis of the approximate coefficient for a normal healthy person is higher than that of Apnea patient up to level 4. At level 7, Kurtosis of the approximate coefficient is higher for the Apnea patient than that of the normal person. Up to level 6, Kurtosis values of detailed coefficients for the Apnea patients are less than that of the normal person. Area of Radar of Kurtosis values for Apnea patient is much less than that of a normal person.

The peak value of Histogram of ECG signals for a normal person is higher than that of Apnea patient, whereas the peak of histogram of the approximate coefficient of Apnea patient is higher than that of a normal person. The specific outcome described here has been presented in Table 5.

9. CONCLUSION

In this paper, DWT-based Kurtosis of ECG signal has been assessed for the diagnosis of Apnea. This has been done by using ECG signals captured from normal persons and Apnea patients. Signals are de-noised by passing them through a well-known Savitzky–Golay FIR filter and then kurtosis values of approximate and detailed coefficients at different DWT decomposition level are determined and compared. Radars of kurtosis are formed, which show a distinct difference in their shape and area. Then, a histogram analysis is done, which shows an increase of its peak value for Kurtosis for Apnea patients. The comparative results may be useful for easy and effective diagnosis of Apnea disease by Kurtosis, radar and histogram analysis, which requires less memory space and may be extended for assessment of other diseases also.

Conventional methods are mainly based on a time domain analysis where the magnitude of different parts of ECG signals and time parameters are monitored. The method proposed is based on wavelet transformation, where analysis is done in the time-frequency domain, considering the non-stationary behavior of the ECG signals. The advantage of the proposed technique is the effective use of a discrete-wavelet-transformation-based statistical parameter in the analysis of ECG signal. As ECG signals are non-stationary, therefore, wavelet transformation is suited, which give information in the time-frequency domain. As the present-day data capture is done in digital format, the use of discrete wavelet transform is found the effective option. Use of few statistical parameters reduces the size or space that is needed to monitor ECG signal in a continuous manner. Medical society may be benefited from this for easy classification of ECG signals having heart disease from the normal. Limitation of the work presented here is that only one disease has been isolated from normal. To overcome this limitation, the work may be extended to include more different types of heart diseases. A comparative study may be extended considering other methods used for diagnosis of Sleep Apnea.

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APPENDIX

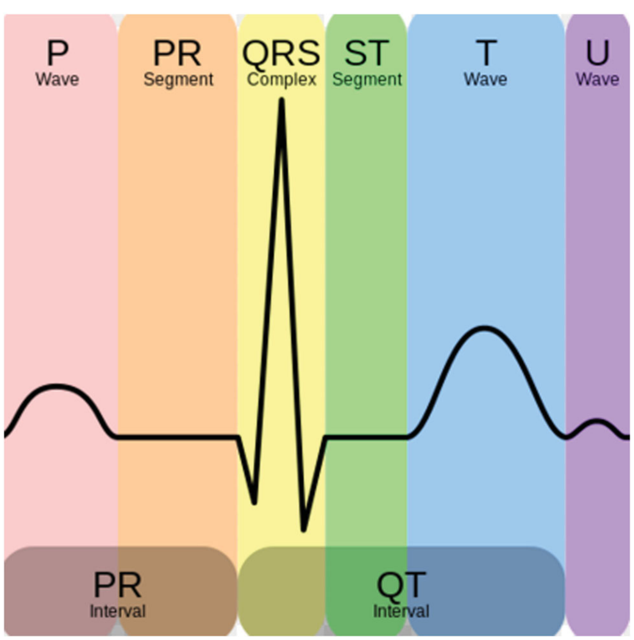

Figure A1: Conventional parameter useful for characterization ECG Signal

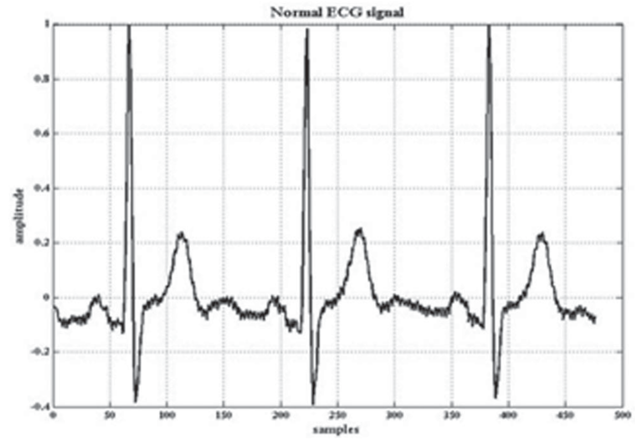

Figure A2: Sample ECG Signal of normal person

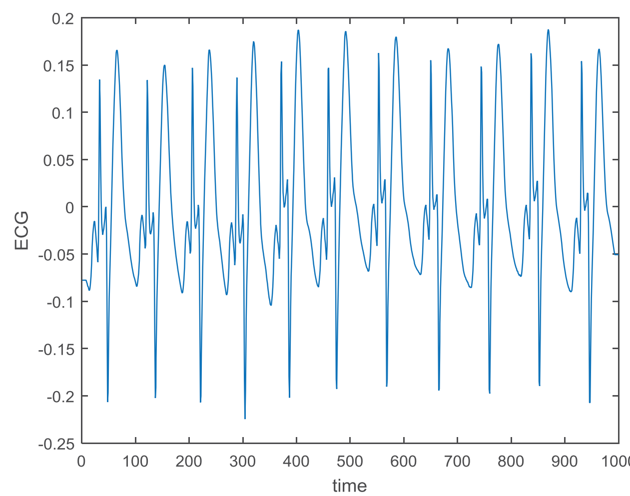

Figure A3: Sample ECG Signal of Apnea Patient

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