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Electrocardiogram Signal Analysis for Diagnosis of Apnea

S Chattopadhyay*, S Chattopadhyay**, A Das***

*Netaji Subhas Open University, Kolkata, India (sansur12ct@yahoo.com)

** Ghani Khan Chowdhury Institute of Engineering & Technology, West Bengal, (surajitchattopadhyay@gmail.com)

*** Jadavpur University, Kolkata, India (adas_ee_ju@yahoo.com)

Abstract

Electrocardiogram (ECG) signal analysis has been done for diagnosis of apnea disease. Some useful statistical parameters are extracted from electrocardiograms and assessment is done. ECG signals are collected from normal healthy persons as well as patients who are suffering from apnea disease for assessment. First, normal ECG signal is collected and then de-noised. Then the signal is decomposed at different levels of discrete wavelet transform (DWT) and approximate coefficients of the normal ECG signal at different DWT decomposition level are determined. Similarly, ECG signals collected from patients suffering from apnea disease are also de-noised. Then, approximate coefficients of this signal at different DWT decomposition levels are determined. Radars and histogram analysis are done both for normal person and apnea patient. Comparative study results in clear changes in those parameters that may be used for detection of apnea.

Key words

Apnea, Approximate Coefficient, Electrocardiogram, Histogram, Radar, Skewness, wavelet decomposition

1. Introduction

With the increase of diversity in human lifestyle, number of Apnea patients is increasing day by day. Research is going on to study causes of apnea, its effect and its relation with electrocardiogram (ECG). Electrocardiogram (ECG) signal has been used for diagnosis of different heart diseases. Rough set decision system has been introduced for classification of different heart diseases [1]. New method has been introduced to detect obstructive sleep apnea using neural network classification of time-frequency plots of the heart rate variability [2]. Portable Holter recorder has been designed with MMC memory for prephase sleep-apnea diagnosis [3]. Sleep apnea screening has been done by autoregressive models from a single ECG lead [4]. Multivariate analysis of blood oxygen saturation has been done for obstructive sleep apnea diagnosis [5]. Real-time approach has been made for detection of apneas on a PDA [6]. A wireless ECG sensor and a low-complexity screening algorithm have been developed for obstructive sleep apnea detection [7]. Sleep apnea diagnosis has been done via single channel ECG feature selection [8]. Unconstrained video monitoring of breathing behavior has been done and then applied to diagnosis of sleep apnea [9]. Unconstrained sleep apnea monitoring has also been done using poly-vinylidene fluoride film-based sensor [10]. An automatic screening approach has been introduced for obstructive sleep apnea diagnosis based on single-lead electrocardiogram [11]. ECG classification has been done for sleep apnea detection [12]. Computer-aided sleep apnea diagnosis from single-lead electrocardiogram has been done using dual tree complex wavelet transform and spectral features [13]. Sleep apnea screening device has been introduced with time-domain signal processing and autonomous scoring capability [14].

ECG signals are non – stationary in time domain. New mathematical tools have been introduced for assessment of such non stationary signals [15] – [18]. Wavelet decomposition based different statistical parameters are found to be very effective in this regard [17]-[18]. Recently discrete wavelet decomposition based statistical parameters have been used in assessment of ECG signals [19] – [20]. In this work an attempt has been made to distinguish ECG signals of apnea patients from that of normal persons based on assessment of DWT based skewness of approximate coefficients, Radar & Histogram analysis.

2. Denoising of ECG Signals

Electrocardiogram signals are collected from normal healthy person and patients suffering from apnea. Normal ECG signal is then de-noised by passing the signal it through S-G FIR filter. De-noising up to 15^{th} level (y^{15}) is done. Sample ECG signal is shown in Fig. 1.

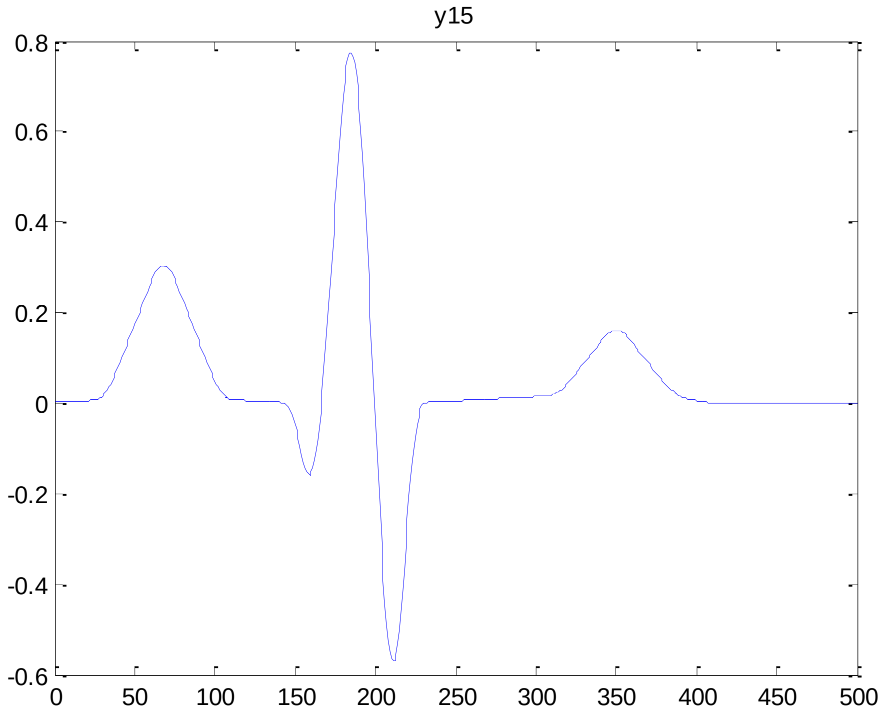


Fig. 1 Sample ECG signal of a normal person

3. Skewness based Assessment

A **Skewness**

Skewness is statistical parameter, mathematically defined as the averaged cubed deviation from the mean divided by the standard deviation cubed. If the result of the computation is greater than zero, the distribution is positively skewed, whereas it's negatively skewed when it's less than zero, and equal to zero means it's symmetric. For univariate data Y_1, $Y_{2,}$ ... ,Y_N, skewness may be mathematical expressed as follows:

$$\mathbf{Skewness} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)S^3}$$

Where $\bar{Y}$ is the mean, S is the standard deviation, and **N** is the number of data points.

B Skewness of Normal ECG Signal

ECG signal is captured from normal healthy person and denoised as shown in Fig. 2. After denoising, normal ECG signal is decomposed at different DWT levels. Then Skewness of approximate coefficients of the normal ECG signal at different DWT decomposition level are measured and presented in Table 1.

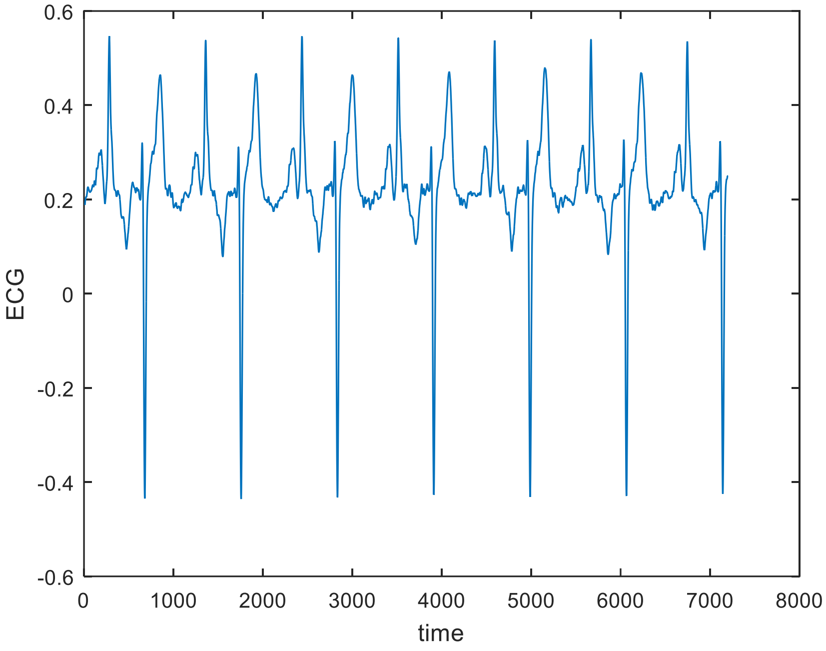


Fig. 2 Denoised ECG Signal of normal healthy person

Table 1

Skewness of approximate coefficients of the normal ECG signal at different DWT levels

DWT level	Skewness of approximate coefficients (SA)
1	-1.90899
2	-1.909
3	-1.90767
4	-1.82983
5	-1.17245
6	0.069502
7	0.45215
8	-0.08327
9	-0.11697

C Skewness of ECG Signal of APNEA Patient

Then ECG signal is captured from patients suffering from apnea disease and denoised as shown in Fig. 3. After denoising, ECG signal of the apnea patient is decomposed at different

DWT levels. Then skewness of approximate coefficients of the ECG signal of apnea patient at different DWT decomposition level are measured and presented in Table 2.

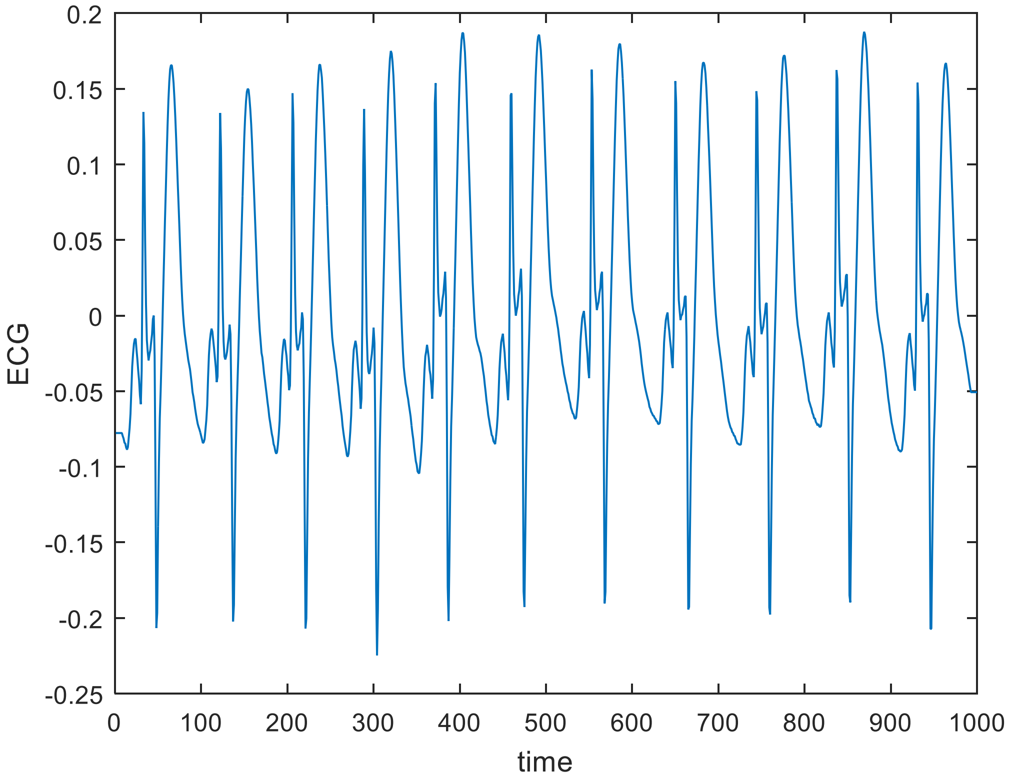


Fig. 3 Denoised ECG signal of apnea patient.

Table 2

Skewness of approximate coefficients of the ECG signal at different DWT level of apnea patient

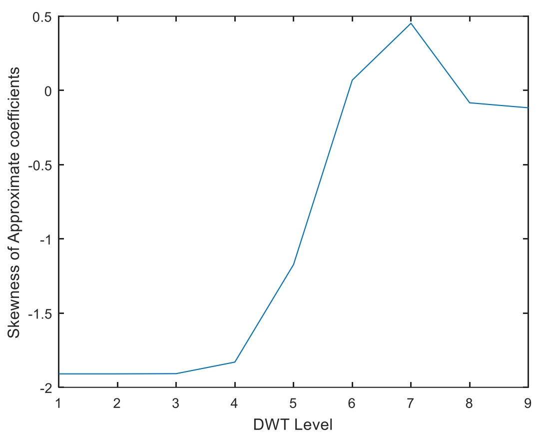
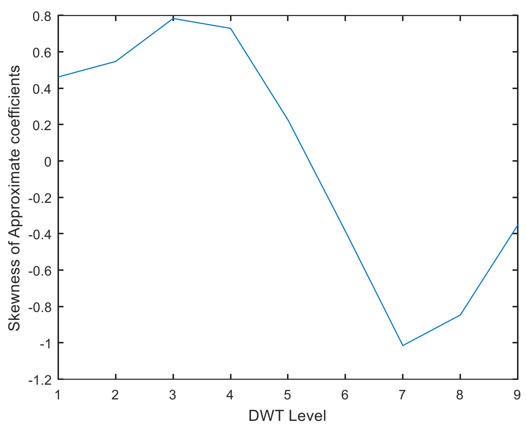
DWT level	Skewness of approximate coefficients (SA)
1	0.462265
2	0.547504
3	0.783677
4	0.72941
5	0.22595
6	-0.38624
7	-1.0147
8	-0.84679
9	-0.3526

D Comparison of Skewness

Then comparative study of skewness of DWT based approximate coefficient has been made as presented in Table 3. It shows that for normal healthy person, skewness of approximate coefficient is low and constant in magnitude up to level 4, then increasing with positive slope up to level 7 and then gradually decreasing. It is maximum at level 7. For apnea patient, skewness of approximate coefficient is comparatively high in magnitude, then decreasing with negative slope up to level 7 and then gradually increasing. It is minimum at level 7.

Table 3

Skewness of approximate coefficient versus DWT levels for normal healthy person and apnea patient

Skewness of approximate coefficient of normal healthy person	Skewness of approximate coefficient of apnea patient
	

4. Radar Assessment

Radars are formed of denoised ECG signals of normal healthy person and apnea patient as shown in Fig. 4 and 5 respectively. Minima and maxima of the radial length are different for radar of ECG of normal person and apnea patient. Radars of ECG show change in shape which may be used for easy isolation of ECG signals of apnea patient from that of normal persons.

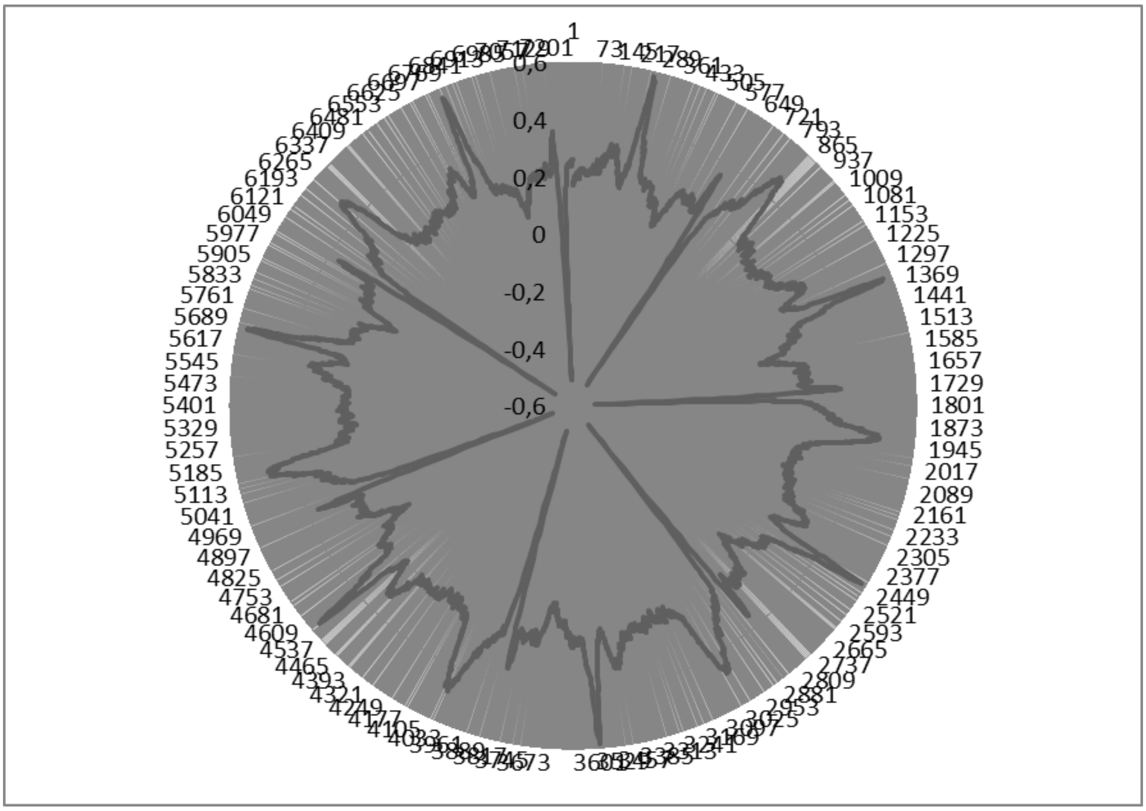


Fig. 4 Radar of ECG signal of normal healthy person

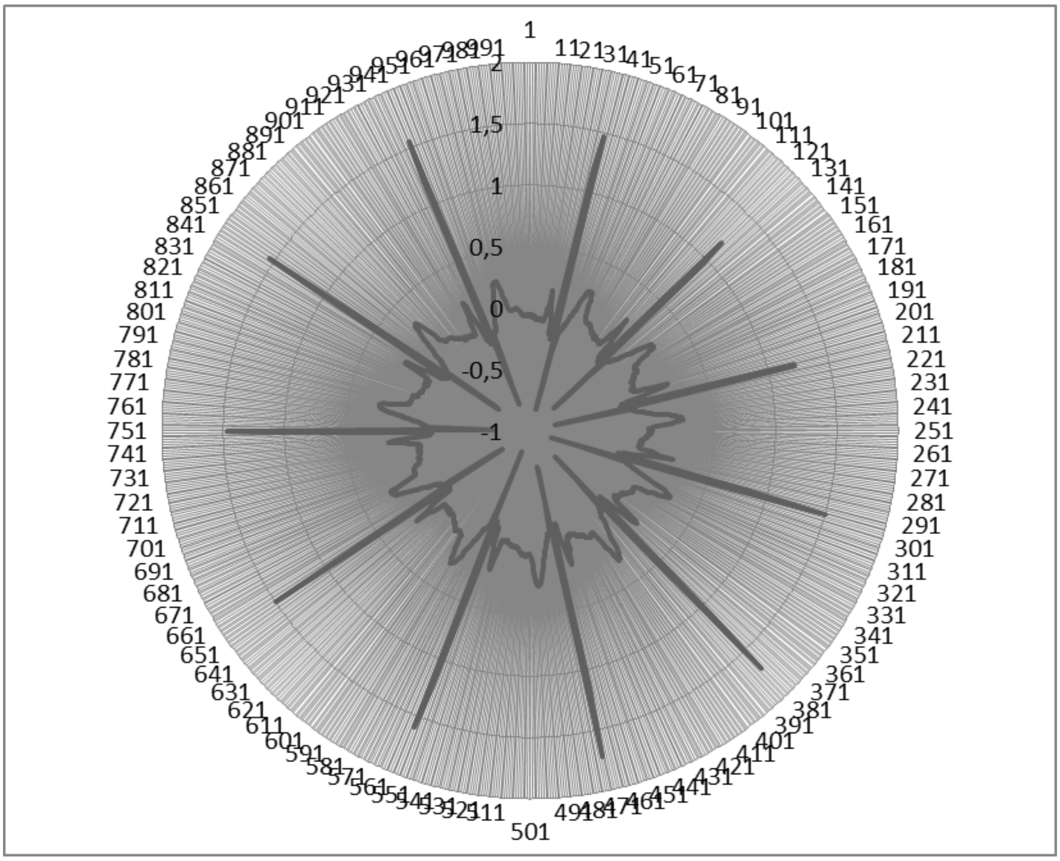


Fig. 5 Radar of ECG signal of apnea patient

5. Assessment of Radar of Skewness of DWT based Approximate Coefficients

Radar of skewness of DWT based Approximate coefficients are then formed of normal healthy person and apnea patient as shown in Fig. 6 and 7 respectively. The radar loop of skewness of approximate coefficient in Fig. 6 is inclined in left half whereas that of apnea patient (Fig. 7) is inclined in right half of the plane. Thus radars show distinct variations in shape which may be used for easy isolation of apnea signals from normal signals.

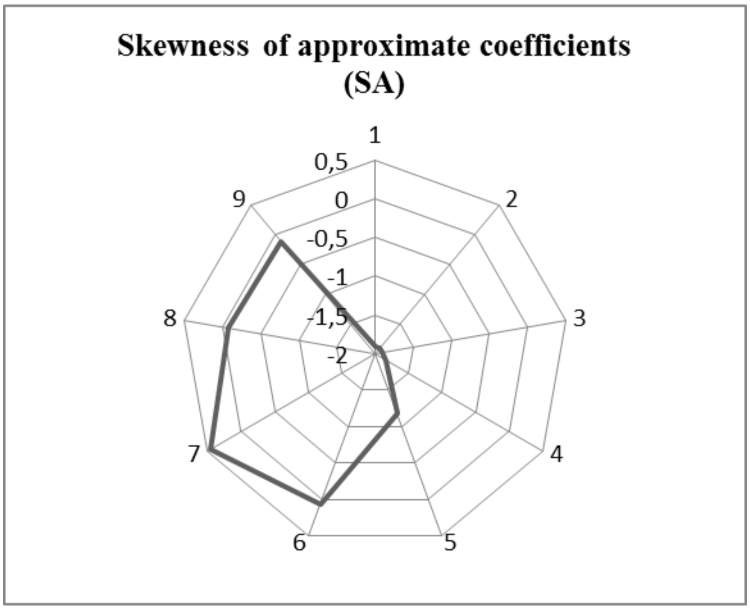


Fig. 6 Radar of skewness of DWT based approximate coefficients of normal healthy person

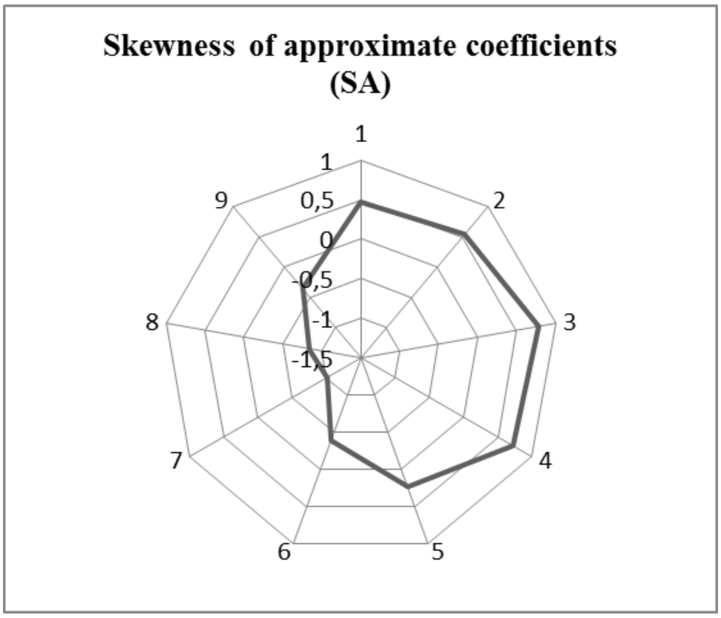


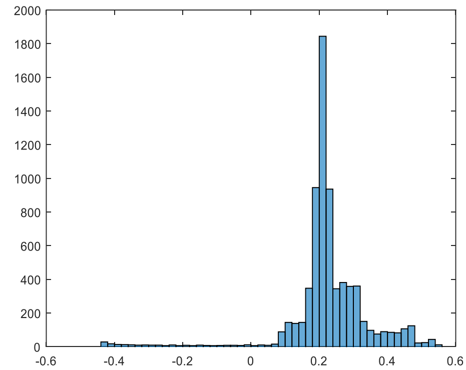
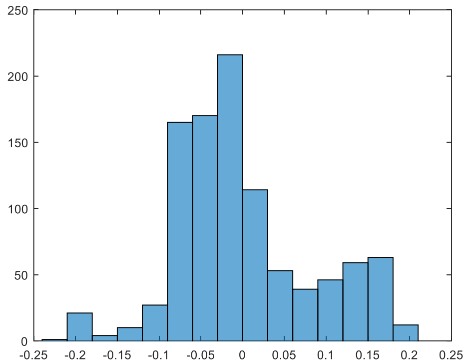
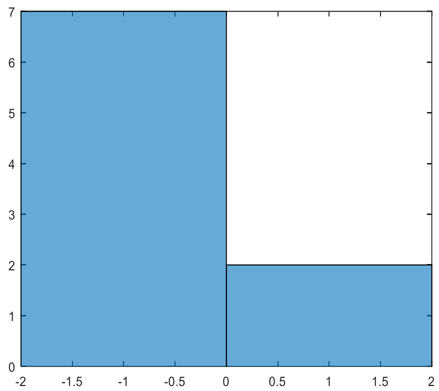
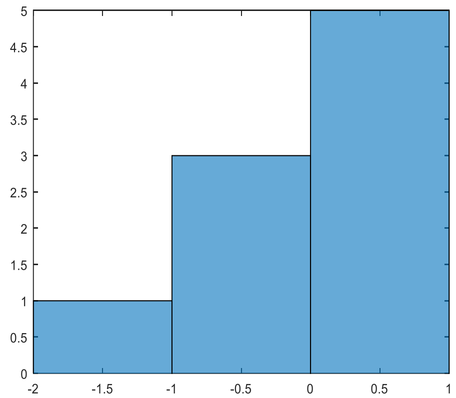
Fig. 7 Radar of skewness of DWT based approximate coefficients of apnea patient

6. Histogram Assessment of ECG Signals and Skewness of DWT based Approximate Coefficients

Histogram of ECG signals and skewness of DWT based approximate coefficients are analyzed both for normal healthy person and apnea patient as presented in Table 4. Histogram of ECG signals show that peak value has decreased for Apnea patient. Number of columns of histogram for skewness is much less than that of ECG signals. However, peak value of the histogram for skewness has decreased for apnea patient.

Table 4

Histogram assessment of ECG signals and skewness of DWT based approximate coefficients of normal healthy person and apnea patient

<table>
<tr><th>Histogram</th><th>Normal healthy person</th><th>Apnea patient</th></tr>
<tr><td>of ECG</td><td>
</td><td>
</td></tr>
<tr><td>of Skewness of Approximate Coefficient</td><td>
</td><td>
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</table>

7. Discussion

In this work, ECG signals are collected both from normal persons and apnea patients. After discrete wavelet transform, approximate coefficients are determined and then skewness is calculated. For normal healthy person, its value is low and constant in magnitude up to level 4, then increasing with positive slope up to level 7 and then gradually decreasing. It is maximum at level 7. For persons suffering from apnea, it is comparatively high in magnitude, then decreasing with negative slope up to level 7 and then gradually increasing. It is minimum at level 7. Then, radars of denoised ECG signals are formed. Minima and maxima of the radial length are seen to be different for normal person and apnea patient. Then, radar loop of skewness of approximate coefficient for normal person and apnea persons are compared. For normal person it is inclined in left half whereas it is inclined in right half for apnea patient. Then, histogram of ECG signals and skewness of approximate coefficients are formed. Its peak value has decreased for apnea patient in both cases.

8. Conclusion

This work deals with the diagnosis of apnea. This has been done by assessment of ECG signals. ECG signals are collected from a normal healthy person and a patient suffering from Apnea. Signals are then denoised by passing it through well-known S-G FIR filter. Signals are the decomposed at different DWT levels and then skewness values of approximate coefficients are determined. Skewness versus DWT level curves of normal person and apnea patients are compared. Then radar assessment is carried out. Radar loops of ECG signals as well as skewness are formed which show distinct difference in their shape. At last, histogram analysis is done on ECG and skewness of approximate coefficients, which shows lowering of its peak value for apnea patients. Comparison shows significant change in the shapes and positions of radar loops and peak of histograms in presence of apnea, which may be useful for easy diagnosis of apnea disease and may be extended for assessment of other diseases also.

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