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Detection of Sleep Apnea and Snoring from ECG signals by using TQWT

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ABSTRACT

Sleep apnea and snoring are two conceivably genuine sleep disorders. Sleep apnea is characterized by pauses in breathing or infrequent breathing during sleep and snoring is a sound produced due to obstructed air movement during breathing while in sleep mode. The current traditional technique used to diagnose these sleep disorders is polysomnography which is costly and requires human specialists and done in unique labs. Subsequently, there is a need of a more comfortable and less expensive technique to detect such types of disorders. Recently researchers focused on signal processing and pattern recognition as alternative methods to detect them. This paper is focused on the detection of sleep apnea and snoring using ECG signals by applying Tunable Q-Factor wavelet transform (TQWT). The obtained results showed a high degree of accuracy, approximately 85%.

Keywords- ECG Signals , Sleep Apnea, Snoring, TQWT

I. INTRODUCTION

Sleep is a naturally occurring state where a man has lost its aggregate thought against the external condition [1] and all muscles are in quiet state alongside other erotic developments. A person travels through many stages during its sleeping hours, for example, Wake, non-rapid eye movement (NREM) and rapid eye movement (REM). Then again, sooner or later this sleep is prevented on account of some embarrassing practices, mental conditions related with it, generally called sleep disorders that further hack down the idea of rest including napping hours. A various intelligent techniques, methods and frameworks have been adopted by analysts to detect sleep and sleeping patterns along with linked sleep disorders which creates some sort of unsettling influences in sleep [4-7].

this paper, two sleep disorders are inspected like sleep apnea and snoring, in which sleep apnea [2] has an imperative perspective for over the best daytime drowsiness. It is extremely natural, in which a person experiences disturbed breathing while sleeping [3]. This disorder builds the dangers of Type-2 diabetes, cardiovascular infections and additionally death rate from road accidents and so on. A large portion of the sleep apnea cases go undiscovered reason for its working cost, bother and inaccessibility of analysis and testing machines. Along these lines, there are numerous strategies created which utilizes the features of ECG signal for the recognition of sleep apnea. As ECG signal recording is one of the efficient and easier technologies for the detection of sleep apnea disorder. Song et al [13] utilized temporal dependence of ECG signals and discriminative hidden markov model for computer-assisted OSA diagnosis. Chen et al [12] put forward a severity index of OSA and utilized SVM for computer assisted sleep apnea identification. Single lead ECG signals had been utilized as a part of this work. Azarbarzin [8] calculated zero-crossing rate and peak frequency from snoring sound signals and performed classification using LDA. Schlotthauer et al [9] performed empirical mode decomposition of pulse oximetry signals for automated OSAS identification. Hassan et al employed spectral features in signal domain [10] and in the dual-tree complex wavelet transform domain [11] and utilized bootstrap aggregating for automated sleep detection.

In snoring, a sound is passed on because of unsettled air change amidst breathing during sleeping time. Smolen et al [14] proposed the measurement methodology and prototype of a home care sleep scoring device in which quality of sleep was estimated from video-recording subject motion, audio-recorded acoustic effects and from the single-lead ECG being the only electrical signal recorded from the body surface. In [14], it was found that light snorers snored uniformly through all stages of sleep. The most interesting fact was that substantial snorers tend to snore more with maximum snoring force in the rapid eye movement sleep phase than in any other phases of sleep.

All, the above said sleep disorders are sufficient fit to obstruct the physical, psychological, cognitive and motor functionality of human body. With the movement of time, these sleep disorders end up being particularly deadly. Today the main dependable strategy utilized as a part of request to recognize sleep disorder is the polysomnography (PSG) which uses various recordings such as electroencephalogram (EEG), electro-oculogram (EOG), electrocardiogram (ECG), body position etc. [15]. One of the issues that constrain its utilization is the lack of sleep clinics than the need of human experts. Therefore, an easier and less expensive alternative is required. Hence, a method is proposed which processes short duration periods of ecg signals to identify sleep apnea and snoring.

The rest of the paper is organized as follows: Section II deals with the materials and methods used in this paper and then section III deals with the conclusion of paper.

II. MATERIAL AND METHODS

1.1 Acquisition of data: In this paper, the experimental data of ECG signals related to sleep apnea and snoring is acquired from physionet.org.The below Fig.1 represents block diagram of the proposed system.

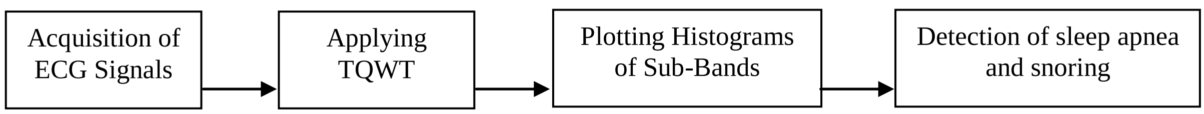

Fig. 1. Block Diagram of Proposed System

1.2 Processing of ECG signals

In this study, a total of 145 patient's ecg signals are taken from physionet database [16], out of which 105 patients belong to sleep apnea and 40 patients to snoring. The following Fig.2 represents ECG signals corresponding to normal, sleep apnea and snoring patients.

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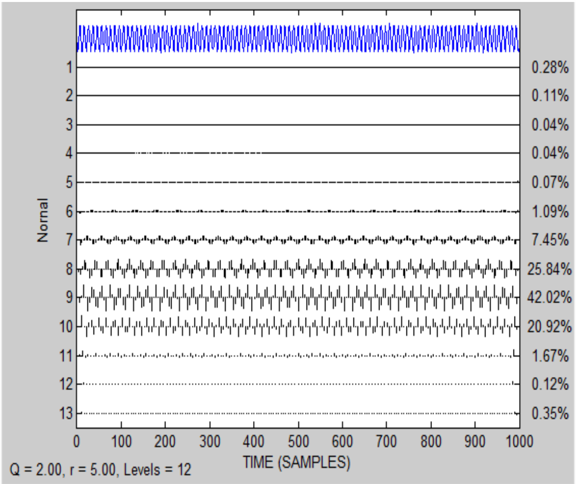
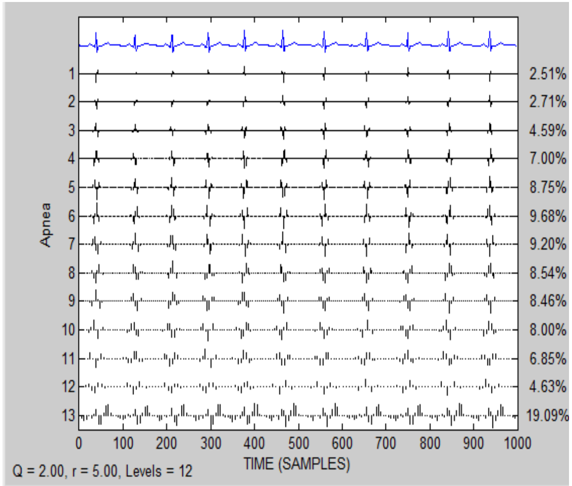
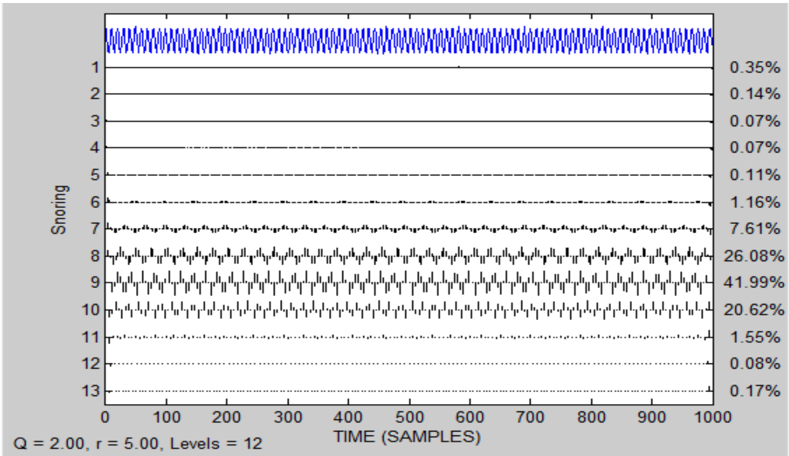


(a)



(b)



(c)

Fig.2 ECG Signals related to normal (a), sleep apnea (b) and snoring patients (c)

To find out the pauses while breathing in sleep apnea and the occurrences of harsh/unpleasant sound caused by the vibration of soft palate in snoring, Tunable-Q factor wavelet transform (TQWT) [17] has been applied which is an adaptable and completely discrete wavelet transform. It is a valuable tool to analyse the oscillatory signals which accomplishes adaptability by changing its input parameters Q-factor Q that controls the quantity of oscillations of the wavelet. Now, the first step is to find out the TQWT parameters Q, R and J [18] which are obtained by verifying Parseval's theorem. This theorem states that the energy of the wavelet coefficients must be equal to the energy of the original signal [18] as described in the below Table. From the table, it has been clearly seen that for R value 5, it follows the Parseval's theorm. Similarly values of Q and J are generated , i.e. 2 and 13 respectively.

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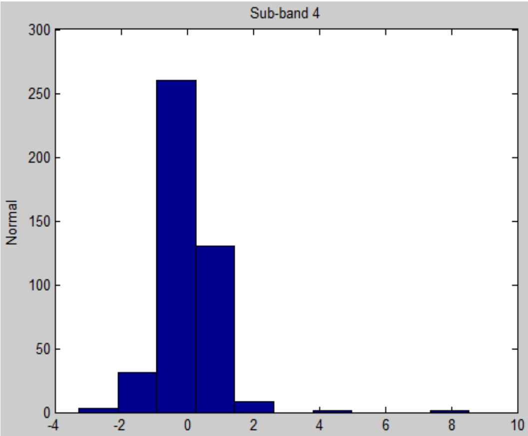
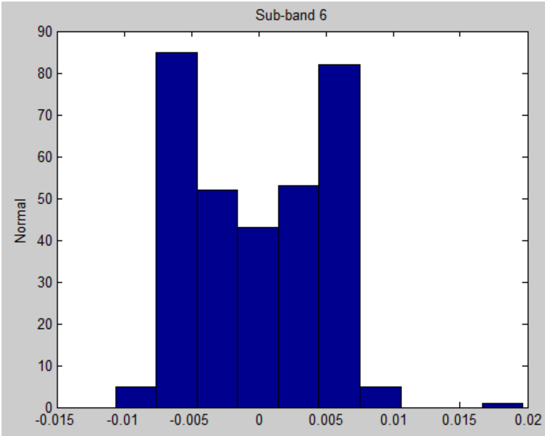
TABLE I Comparison of Wavelet Coefficient Energy and Signal Energy

R Value	Wavelet Energy	Signal Energy
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	5.906875	5.906875
6	11.813750	5.906875
7	17.720625	5.906875
8	23.627500	5.906875
9	29.534375	5.906875
10	35.441250	5.906875
11	41.348125	5.906875
12	47.255000	5.906875

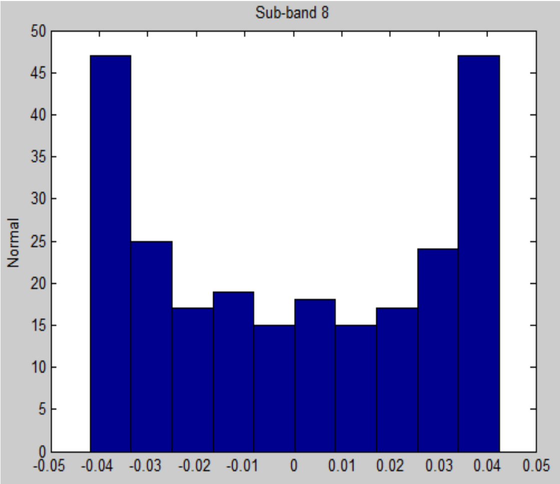
The second step is based on the comparison of sub-bands of the apnea and normal patients as shown in the following Fig. 3. From this figure, it has been clearly depicted that (a) part has less amount of pauses at 0 values than (b) in which a patient is suffering from sleep apnea. Likely, the snore values are computed in case of snoring patients as shown in the below Fig. 3. The histograms of the samples show variations in dispersion and steepness among normal, sleep apnea and snoring.



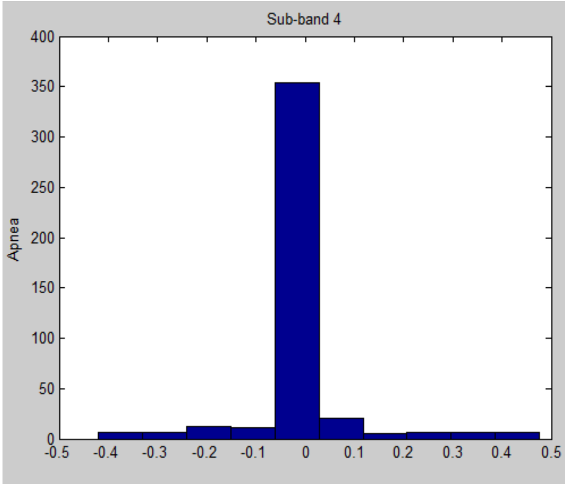
(a)



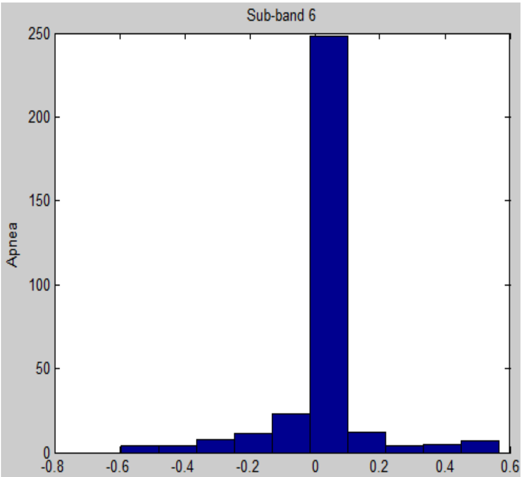
(b)


Sub-band 8
Normal
50
45
40
35
30
25
20
15
10
5
0
-0.05
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
0.04
0.05

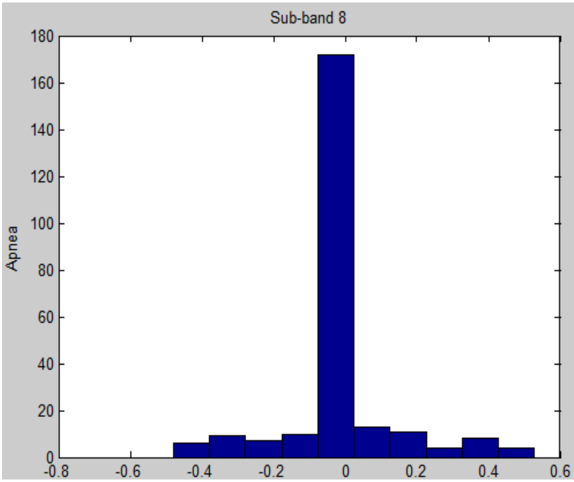
(c)


Sub-band 4
Apnea
400
350
300
250
200
150
100
50
0
-0.5
-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4
0.5

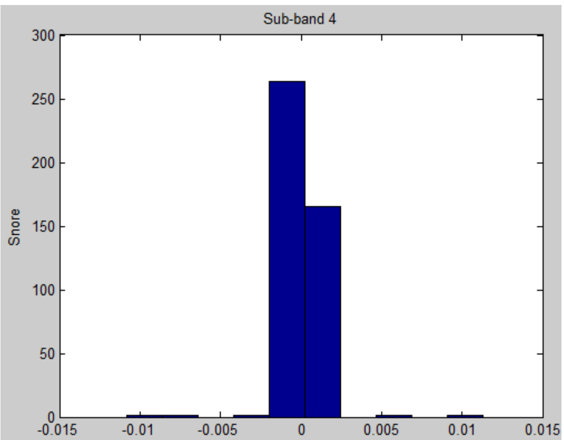
(d)


Sub-band 6
Apnea
250
200
150
100
50
0
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6

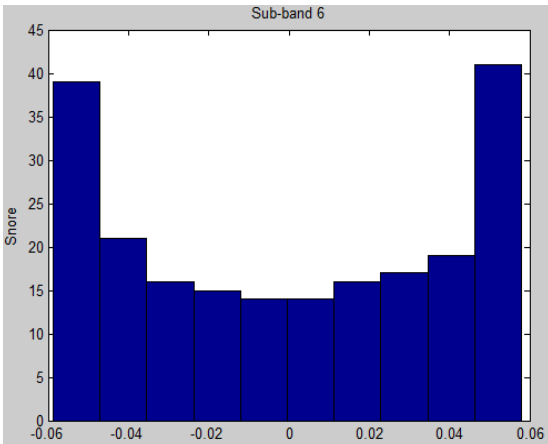
(e)


Sub-band 8
Apnea
180
160
140
120
100
80
60
40
20
0
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6

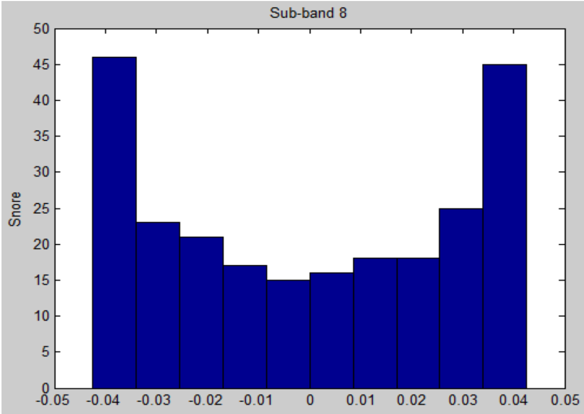
(f)


Sub-band 4
Snore
300
250
200
150
100
50
0
-0.015
-0.01
-0.005
0
0.005
0.01
0.015

(g)


Sub-band 6
Snore
45
40
35
30
25
20
15
10
5
0
-0.06
-0.04
-0.02
0
0.02
0.04
0.06

(h)



(i)

Fig. 3 Histograms of sub-bands (a)-(c) 4,6 and 8 respectively for normal patients, (d)-(f) 4,6 and 8 respectively for sleep apnea and (g)-(i) 4,6 and 8 respectively for snoring patients

III. RESULTS AND DISCUSSION

In this paper an effort is made for the detection of sleep apnea and snoring by applying TQWT. For the observation purpose, ECG signals are collected from Physionet database. From older days to till now, PSG procedure is used to detect the sleep disorders but it is not possible to go through from the PSG procedure due to its high cost factor and need of more human specialists and unique labs. Moreover, it is also a time consuming and cumbersome process. Subsequently, there is a need of a more comfortable and less expensive technique to detect such types of disorders. Hence, ECG signals are used to detect the sleep apnea and snoring. The accuracy achieved in this method is 85% and can be improved with the addition of symptomatic guidelines.

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