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Implementation of TQWT for the detection of Sleep Apnea and Snoring from ECG signals

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Abstract: - **Sleep apnea and snoring are two conceivably genuine sleep disorders. Sleep apnea is defined as pauses while breathing or infrequent breathing at the time of sleep and snoring is a sound delivered because of blocked air development amid 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. As of late analysts concentrated on signal processing and pattern recognition as substitute modes to reveal them. The following research 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%.**

Index Terms- **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 quite 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].

In 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 signals as it is one of the efficient and easier technology used for recognition and detection of sleep apnea. Song et al [13] utilized temporal dependence of ECG signals and discriminative hidden markov model for PC helped OSA findings. Chen et al [12] set forward a seriousness record of OSA and used SVM for PC helped sleep apnea distinguishing proof. Single lead ECG signals had been used as a piece of this work. Azarbarzin [8] computed zero-intersection rate and pinnacle recurrence from snoring sound signals and performed arrangement utilizing LDA. Schlotthauer et al [9] performed observational mode disintegration of heartbeat oximetry signals for computerized OSAS distinguishing proof. Hassan et al utilized spectral features in signal domain [10] and in the double tree complex wavelet transform domain [11] and used bootstrap collecting 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 estimation procedure and model of a home care sleep scoring gadget in which nature of sleep was evaluated from video-recording subject movement, sound recorded acoustic impacts and from the single-lead ECG being the main electrical flag recorded from the body surface. In [14], it was discovered that light snorers wheezed consistently through all phases of sleep. The most fascinating actuality was that significant snorers tend to wheeze more with greatest wheezing power in the quick eye development sleep stage than in some other periods 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

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(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. Henceforth, a strategy is proposed which forms brief span times of ecg signals to identify sleep apnea and snoring. Whatever is left of the paper is sorted out as takes after: Section II deals with materials and methods used in the paper and then section III deals with the conclusion of paper.

II. MATERIAL AND METHODS

A. Acquisition Of Data

In this paper, the experimental data of ECG signals related to sleep apnea and snoring is acquired from physionet.org. The beneath Fig.1 speaks to piece outline of the proposed framework.

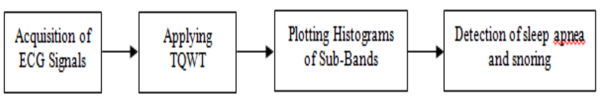


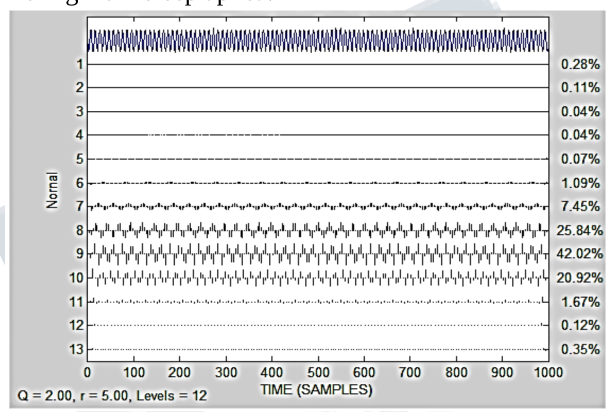
Fig. 1. Block Diagram of Proposed System

III. RESULTS AND DISCUSSION

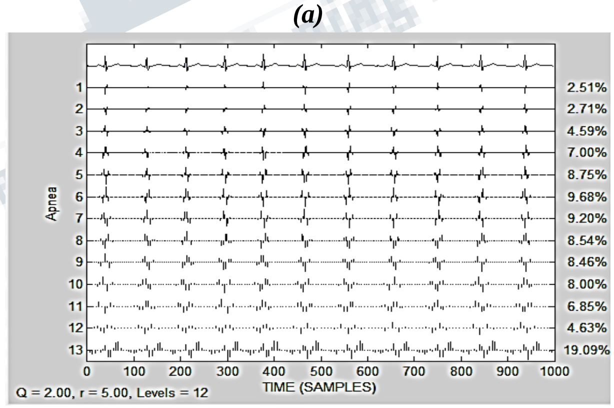
In this paper an effort is made for the detection of sleep apnea and snoring by applying TQWT. For the observation purpose, ECG signals are collected from Physionet database. From older days to till now, PSG procedure is used to detect the sleep disorders but it is not possible to go through from the 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.

A. Processing of ECG Signals

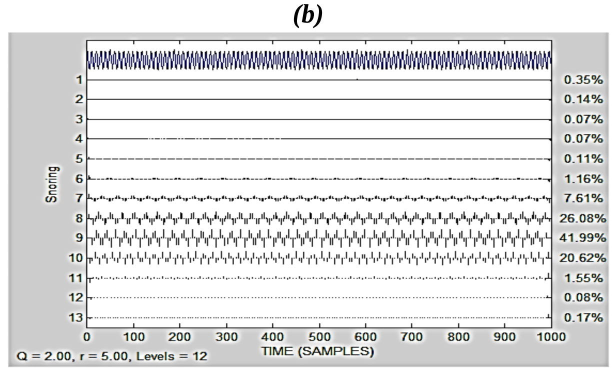
In this study, a total of 145 patient's ecg signals are taken from physionet database [16], out of which 105 patients belong to sleep apnea and 40 patients to snoring. The following Fig.2 represents ECG signals corresponding to normal, sleep apnea and snoring patients. To find out the pauses while breathing 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 an oscillatory signal 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 following Table 1. From table, it has been plainly delineated 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. 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.



(a)



(b)



(c)

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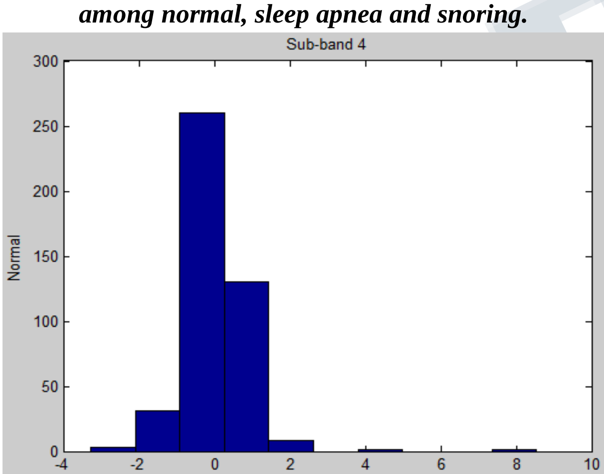
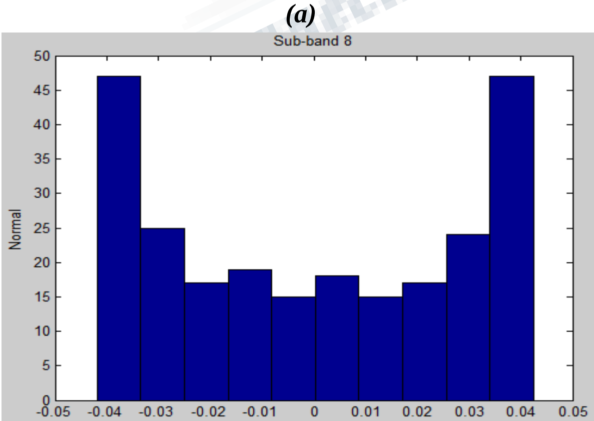
TABLE I : Comparison of Wavelet Coefficient Energy and Signal Energy

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

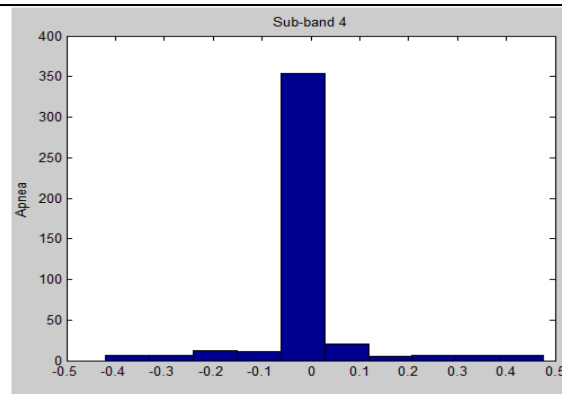
Likely, the snore values are computed in case of snoring patients as shown in the below Fig. 3. The histograms of the samples show variations in dispersion and steepness among normal, sleep apnea and snoring.



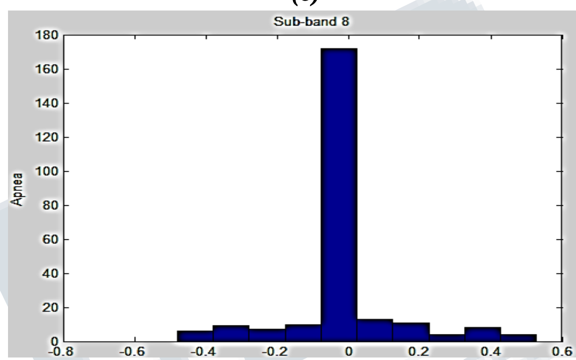
(a)



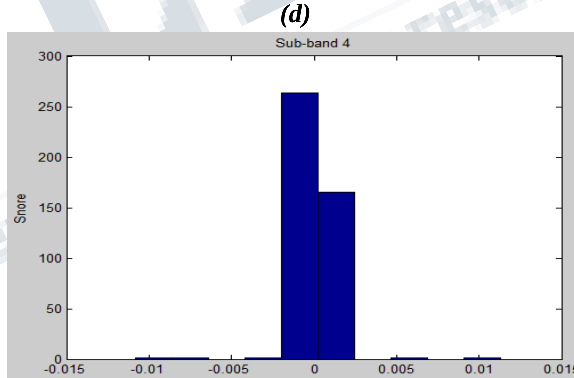
(b)



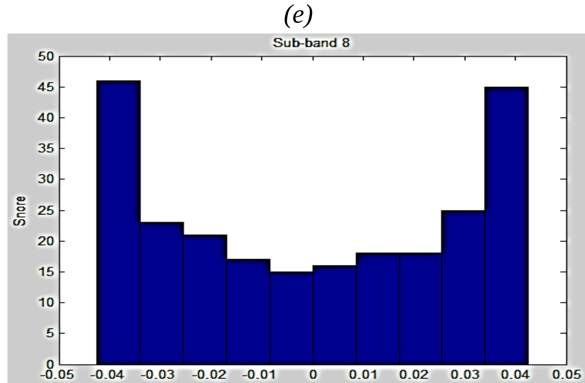
(c)



(d)



(e)



(f)

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

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