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Detection of Sleep Apneathrough ECG Signal Features

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Abstract: A type of sleep disorder is characterized by the breaks in respiratory breathing process or occurrences of uncommon or superficial breathing during sleep is called sleep apnea disorder. Since for the last few years various signals (such as PolySomnoGraphy (PSG) signals, EEG signals, Respiratory signals, ECG signals etc) have been used for the detection of sleep apnea syndrome or disorder. But ECG signal recordings have been found effective and efficient for the diagnosis process. Various models and algorithms have been developed using ECG signal recordings to detect sleep apnea disorder. Sleep apnea is a sleep related breathing disorder that affects middle aged adults. Most of sleep apnea cases are currently undiagnosed. Due to expenses and limitations of Polysomnography at sleep labs. In new techniques for sleepapnea classification are being developed for most comfortable and timely detection. Which processes short duration epochs of the electrocardiogram data.The automated classification algorithm are based on Support Vector Machines (SVM) and tested for apnea recordings? ECG signal is the most important and powerful tool used contains the diagnosis and treatment of heart diseases. ECG signal represents electrical activity of the heart. The accurate ECG interpretation is required to evaluate the valuable information inside the ECG signal.

Key words: ECG · QRS Detection · R Peak Detection · Pan Tompkins Algorithm · SVM · PSG

INTRODUCTION

Sleep apnea is found in 10% of middleagedadults.In long term ithas effect on cardiovascular system.Sleep study (PSG) is a long term process were the patient is observed for the whole night and the respiratory signals are observed.

In most of the cases this sleep study is not a comfortable process. Sleep apnea is the intermittent cessation of airflow at the nose and mouth during sleep. Apneas that last for at least 10s duration important but in most cases the apneas last 20-30 sand can last as long as 2-3min. Sleep apnea is the leading cause of daytime sleepiness and contributes to CVS(Cardio Vascular System) disorder [1-8]. By using ECG signal features here, is to overcome most of the negative factors in detection of sleep apnea.

Sleep Apnea: The brain is very active during sleep. Different type of brain wave is activity forrecognized in different stages of sleep. The average lifespan, humans sleep for about one third of their lives. Same as eating and drinking, sleeping is necessity for our body. The essential prerequisite of mental and physical health is good sleeping. The sleep time body renovate itself. The body cannot function well without enough sleeping. Lack of sleep can be damage the body physically, emotionally and psychologically.A type of sleep disorder due to uncommon breathing during sleep known as sleep apnea. Each break in breathing is named Sleep apnea is break in the respiration and can cause damage to functioning of heart in long term. Most cases go undiagnosed because of inconvenience, operating cost and unavailability of testing. Test are time consuming for person has to stay whole night for sleep study.

Electrocardiogram (ECG): Electrocardiogram is the representation of the electrical activity of heart recorded by skin electrode. Each activity has a distinct waveform. The morphology and heart rate reflects cardiac health of human heart beat. It is non-invasive technique is measured on the surface of human body, which is used for the identification of the heart diseases [7]. Any disorder of heart rate in the morphological pattern is

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indication of cardiac arrhythmia. Which could be analysis of the recorded ECG waveform? Normal ECG wave form consists of P wave,QRS complex and T-wave. The amplitude and duration of P-QRS-T wave contains useful information for the nature of disease associated with the heart [4]. The electric wave is depolarization and re polarization of Na+ and K+ ions in the blood. The ECG signal provides the following information of a human heart.

- Heart position and its relative chamber size
- Impulse origin and propagation
- Heart rhythm and conduction disturbances
- Extent and location of myocardial ischemia
- Changes in electrolyte concentrations
- Drug effects on the heart.

Evaluating ECG signals in 30 seconds interval is time consuming even for experience physician [5, 6]. So these signals are recorded in digital form and the diagnosis is made directly from these records, so they are suitable for automatic processing [9, 10].

The aim of the project is to automatically classify sleep stage and sleep apnea using only the electrocardiogram (ECG) records and to find if conditions of sleep apnea (or other sleep disorder) are fulfilled for each analysed interval. The standard ECG signal has 12 leads: which includes 3 bipolar leads, 3 unipolar leads and 3 chest leads [2]. A lead is a pair of electrodes (+ve& -ve) placed on the body in designated & connected to an ECG record.

Waves Representation

P wave: Amplitude level of this voltage signal wave is low and represent depolarization and contraction of right and left atria. A clear P wave before the QRS complex represents sinus rhythm. Absence of P waves are suggest atrial fibrillation, ventricular rhythm. It is difficult to analyse the P waves with high signal-to-noise ratio in ECG signal.

QRS Complex: The QRS complex is largest voltage deflection is approximatelyabout 10– 20 mV but may varying size depending on age and gender. The voltage amplitude of QRS complex is give information about the cardiac disease. Duration of the QRS complex indicates time for the ventricles to depolarize may give information about conduction problems in the ventricles such as bundle branch block.

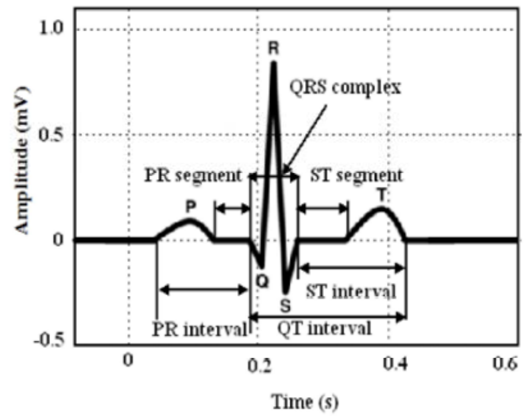

Fig. 1: Schematic representation of normal ECG waveform

Table I: Amplitude and duration of waves, intervals and segments of ECG signal.

S.No.	Features	Amplitude (mV)	Duration (ms)
1	P wave	0.1 – 0.2	60 – 80
2	PR – Segment	-	50 – 120
3	PR – Interval	-	120 – 200
4	QRS Complex	1	80 – 120
5	ST – Segment	-	100 – 120
6	T – Wave	0.1 – 0.3	120 – 160
7	ST – Interval	-	320
8	RR – Interval	-	(0.4 – 0.2)s

T Wave: It represents the ventricular repolarization.Large T waves may represent ischemia and Hyperkalaemia.

The Table I. shows features of P-wave, QRS complex and T wave in maximum amplitude and its duration. According to medical definition the duration of each RR-interval is about 0.4-1.2s.

Sleep Apnea and Ecg Signal Affiliation: In recent times sleep apnea has become one of emerging disorders for hypertension, insomnia, heart diseasesand some other diseases too. To detect sleep apneaECG is considered as efficient features. Cyclic variations for duration of heartbeat, also known as RR intervals (time interval from one R wave to next R wave) of ECG have reported to associated with sleep apnea episodes. These fluctuations within the individual’s cardiovascular system expressed bybradycardia during apneais tachycardia upon its cessation. The accurate measurement of ECG is done by an automated classification algorithm that uses Support Vector Machines (SVM) are a powerful method for pattern classification [11, 12]. Basic idea is to map data is high-dimensional space and find a separate hyperplane with maximal margin. When SVM uses classifier acts as an automatic classifier (SVC).

QRS Complex Detection: A QRS detection time is defined as the time occurrence of the QRS complex in an ECG signal. QRS detection time is generated automatically for all the recordings using an algorithm. The algorithm provides detection times, which occur close to the onset QRS complex. A second set of QRS detection was formed after manual verification and correction of the first. The two sets are used separately to generate feature and determine the importance of QRS detection on classification accuracy. QRS part of an ECG is an important part of ECG analysis. Pan Tompkins algorithm of QRS detection is an established method for the extraction of the particular part of ECG. A modification has been done for Pan Tompkins algorithm by using Savitzky-Golay filter in the place of the high pass filter and differentiator of Pan Tompkins algorithm.

Wavelet Transform: The wavelet transform is convolution of the wavelet function ψ(t) with the signal x(t). Orthonormal dyadic discrete wavelets are associated by scaling functions φ(t). The scaling function can be convolved with the signal to produce approximation coefficients S. Therefore discrete wavelet transform (DWT) can be written a

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)\mathrm{d}t \tag{2.1}$$

By choosing an orthonormal wavelet basis $\psi_{m,n}(t)$ we can reconstruct the original. The approximation coefficient of signal at scale m and location n can be written as

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\phi_{m,n}(t)\mathrm{d}t \tag{2.2}$$

But discrete input signal is of finite length N. The range of scales that can be investigated is $0 < m < M$. A discrete approximation of the signal can be written as

$$x_0 = x_M(t) + \sum_{m=1}^{M} d_m(t) \tag{2.3}$$

where the mean signal approximation at scale M is $x_m(t) = S_{m,n}\varphi_{m,n}(t)$ and detail signal approximation corresponding to scale m, for finite length signal isgiven by

$$d_m(t) = \sum_{m=1}^{M-m} T_{m,n}\,\psi_{m,n}(t) \tag{2.4}$$

The signal approximation at a specific scale is combination of approximation and detail at the next lower scale.

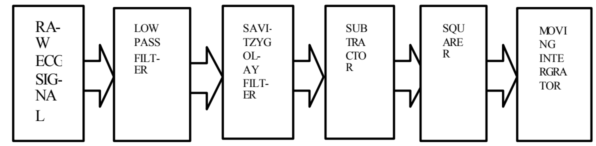

Fig. 2(a): QRS Detection Using Savitzky-Golay Filter

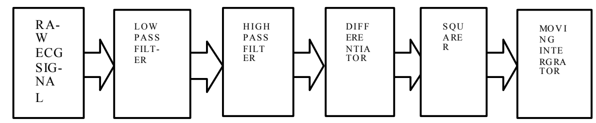

Fig. 2(b): Pan Tompkins algorithm block diagram.

$$X_m(t) = x_{m-1}(t) - d_m(t) \tag{2.5}$$

Hence for filtering and to extract the proper ECG signal the transformation is used.

Filtering: The main function of the stage is to increase the signal to noise ratio of the ECG signal is emphasizing the QRS complex. A band pass FIR Butterworth filter is pass band frequencies of 5-15 Hz is used to removedpower-line interference and high frequency noises from the original signal.

Savitzky-Golay filter shown in Figure 2.(a) has been used both for ECG noise reduction and compression. It has been used to signal following capabilities by least squares approach [12].

Pan Tompkin's Algorithm: The band pass filter that has been used low pass filter and then a high pass filter in cascade. The low pass filter is to suppress high frequency noise. Filter design uses digital filters having integer coefficients allows real time processing speeds. The floating point processing required speed is high.QRS energy is maximised by the pass band of approximately 5 to 15 Hz range. The filter is an integer filter is poles located such so as to cancel out each other and shown in Figure 2.(b).

Differentiation of the signal is done and it has been through the band pass filter. Squaring the signal is to be squared. This is the non-linear processing of the signal.It is done and get all positive values later these values can be processed the corresponding squared waves. Also this processing emphasizes higher frequencies of the ECG signal which are due to the presence of the QRS complexes.The slope of the R wave is absolute way to detect QRScomplexes in an ECG. There are many long duration and large amplitude QRS waves in the ECG signal is abnormal. Only slope of R wave can't detect the waves.A moving window integrator is used so that these waves can be detected as well.

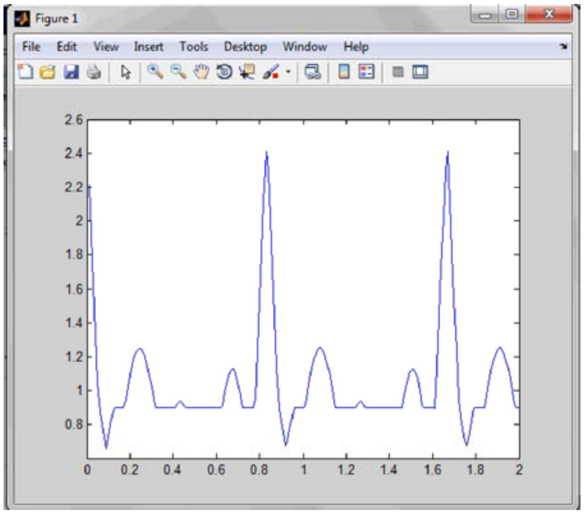

Fig. 3(a): Simulation for Heartbeat Rate 72/Sec

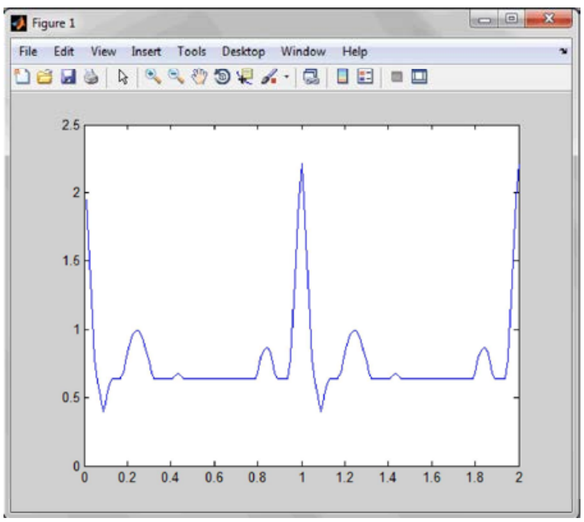

Fig. 3(b): Simulation for Heartbeat Rate 60/Sec

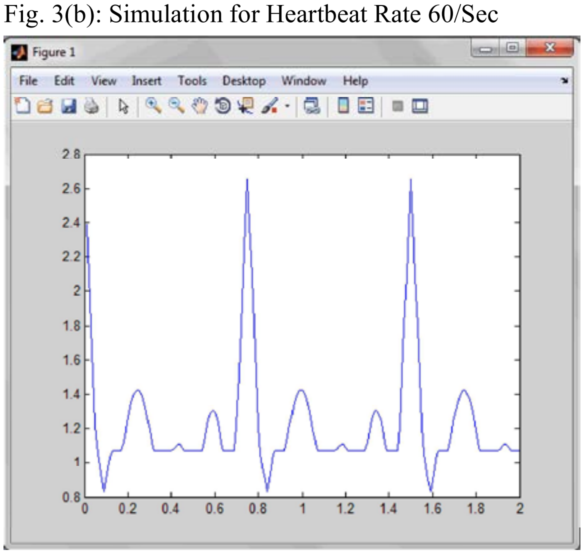

Fig. 3(c): Simulation for Heartbeat Rate 80/Sec

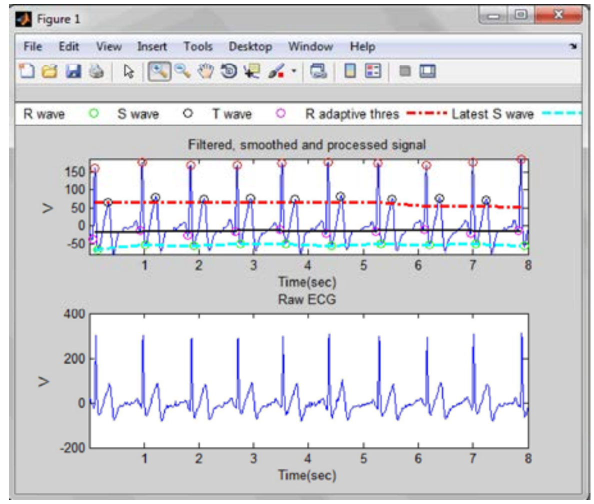

Fig. 3(d): Output for QRS Detection

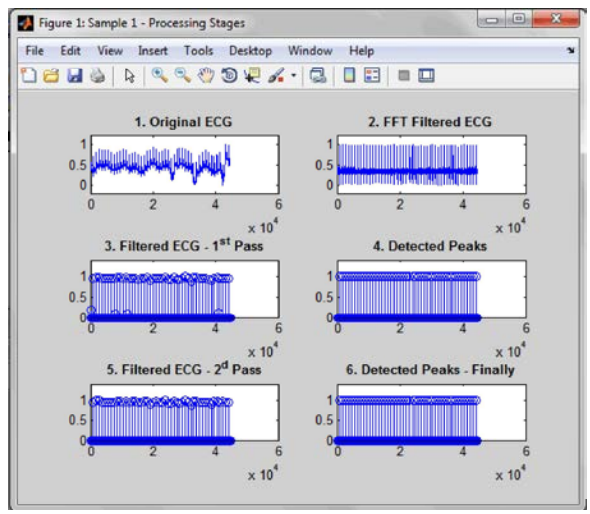

Fig. 3(e): ECG Signal Filtering for Normal and Abnormal

RESULTS AND DISCUSSION

Output for ECG Signal: The Figure 3.(a) shows the waveform simulated for 72beats per second heart rate, which is the normal ECG wave of any person and PQRS peaks are obtained.

The Figure 3.(b) details the waveform simulated for little lower heart rate of 60 beats per second and shows abnormality in PQRS peaks when compared with previous normal ECG. Person may have low blood pressure, sleep apnea, anaemia and other cardiac disorders.

The Figure 3.(c) represents the waveform of little higher peaks from normal heart rate of about 80 beats per second and hence changes in the PQRS peaks are shown.

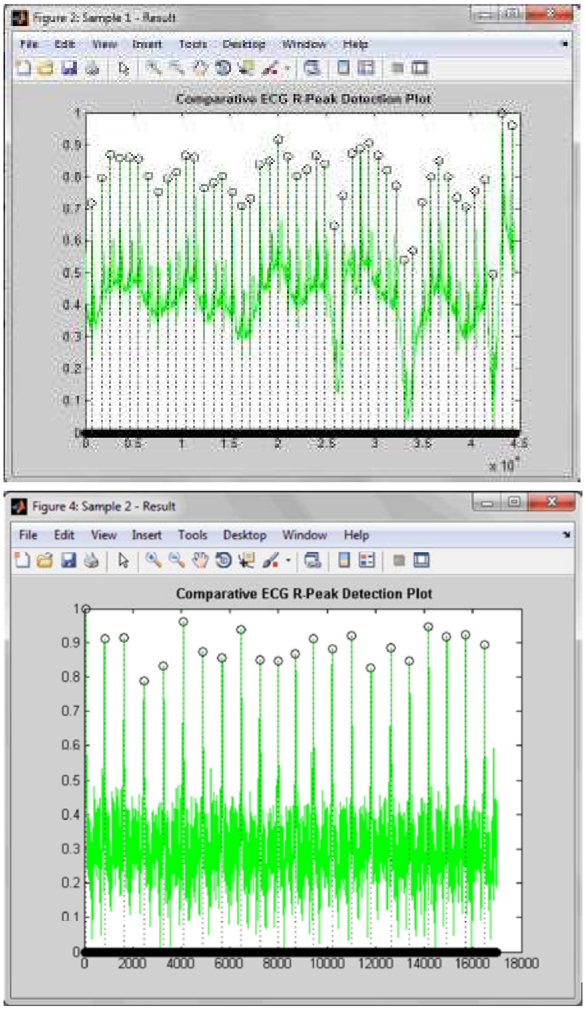

Fig. 3(f): ECG Signal using R peak Detection Plot

In the above Figure 3.(d) the raw ECG signal generated using QRS detection algorithm is filtered and smoothed for elimination of noise and then the processed signal is obtained.

The filtering of both normal and abnormal ECG signal is done by taking the FFT of the filtered ECG signal and the signal is filtered using two pass filters then R peaks are detected and shown in Figure 3.(e).

The Figures 3.(f).shows the plot for two different samples of ECG signals and differences of the two R-peaks can be obtained by comparison of both the plots.

CONCLUSION

In this paper observed that QRS detection is possible with higher amplitudes of the detected QRS peaks. The algorithm also eliminates the need of the high pass filter and differentiator blocks.The classification accuracy can improve by extracting the better features of ECG signal. Future developments can be made as follow design better feature extraction methodology which can improve the classification result of cardiac arrhythmias in ECG signal. To analyse the classification accuracy using different classifier such that it can classify the beat arrhythmias in the approved manner. To modify the network structure according to cost function of multilayer neural network so that it can achieve better classification accuracy as compared to existing ECG beat classifier.Real time operation for recognizing the cardiac arrhythmias can also be done since the methodology uses the automatic detection of R-peaks and feature extraction techniques.

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