Android Based Sleep Apnea Monitor

Ajmal M Ali
Roll No : 02
Department of Electronics And Communication
Model Engineering College
Thrikkakara

INTERNAL GUIDE : Mr. JAGADEESH KUMAR P
EXTERNAL GUIDE : Mr. M R BINUMON

30th April 2015

Declaration

I hereby declare that the submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the report.

Place: Thrikkakara

Date: April 30, 2015

Signature

Name: Ajmal M Ali

Reg.No : 98914067

Acknowledgement

This work would not have been possible without the support of many people.

First and the foremost, I give thanks to Almighty God who gave me the inner strength, resource and ability to complete my project successfully.

I would like to express my sincere thanks to our Principal, **Dr. V.P. Devasia**, for his valuable support and advice. I would also like to thank our HOD, **Dr. Jayasree V.K** for her valuable help and support. I express my gratitude to our M.Tech co-ordinator and my guide **Mr. Jagadeesh Kumar P** for his guidance and help. I wish to express my sincere gratitude to my project co-ordinator **Mrs. Anjana Devi S** for her advice and support. I also wish to thank **Dr. Mini M G** for her advice and support.

I would also like to thank **Mr. M R Binumon**, Project manager, Amigo Medical Systems, Ernakulam for all their help and directions which helped me to step forward with confidence and self belief.I an greatly obliged for all the valuable suggestion and constant guidance they provide in realizing this project.

I am indebted to all the staff of the Department of Electronics Engineering for their co-operation and support.Last but not the least I wish to express my sincere thanks to all my friends for their goodwill and ideas.

Abstract

Sleep Apnea is the instance when one has pauses of breathing in their sleep. Obstructive sleep apnea(OSA) is the common form of sleep apnea which is currently tested through polysomnography(PSG). PSG got many criticisms from some researchers. This is due to several reasons, including uncomfortable, expensive, and limited availability. Therefore a need for simpler technology that has the same reliability with PSG that doesn't require special laboratory is long over due. This project focuses on the analysis of ECG signal for the estimation of sleep apnea in an Android platform. For this a Pan Tompkin algorithm is used for the QRS detection and RR interval estimation. The estimated RR interval is used for extracting different parameters for the detection of sleep Apnea.

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List of Abbreviations

ADB	Android Debug Bridge
ADT	Android Development Tools
AHI	Apnea Hypopnea Index
CSA	Central Sleep Apnea
CVHR	Cyclic Variation Of Heart Rate
CWT	Continuous Wavelet Transform
ECG	Electrocardiogram
EEG	Eectroencephalogram
EMG	Electromyogram
EOG	Electroocculogram
HR	Heart Rate
IDE	Integrated Development Environment
JRE	Java Runtime Environment
NREM	Non Rapid Eye Movement
OS	Operating System
OSA	Obstructive Sleep Apnea
PSG	Polysomnography

REM	Rapid Eye Movement
SDK	Software Development Kit
WHO	World Health Organisation

Chapter 1

INTRODUCTION

Sleep is defined as the naturally recurring state of rest during which consciousness of the world is suspended. Sleep can be categorized into two types: Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM). REM and NREM sleep alternate cyclically through the night. NREM sleep is further divided into four stages (NREM 1 to NREM 4)[13]. A sleeping disorder is when one cannot sleep, causing the body to lose function. Just as the bodys benefits of rest can range from physical to emotional and psychological effects, lack of sleep can damage the body physically, emotionally and psychologically. To date 84 kind of sleep disorders have been discovered, where insomnia, Sleep Apnea, narcolepsy, and restless leg syndrome are the most common sleep disorders[11] .

Sleep Apnea characterized by abnormal pauses in breathing or instances of abnormally low breathing during sleep. Each pause in breathing, called an apnea, can last from a few seconds to minutes, and may occur 5 to 30 times or more an hour. Some of the symptoms that sleep apnea patients commonly display include snoring, pauses in breathing during sleep, choking or gasping for air following breathing disturbances, daytime sleepiness while carrying out routine tasks, headaches, dryness of throat in the morning, lack of concentration ability, urination at night, depression and irritability, and obesity[7].

Similarly, each abnormally low breathing event is called a Hypopnea. Sleep apnea is typically divided into two classes; central sleep apnea (CSA) in which respiratory drive is absent or inhibited, and obstructive sleep apnea (OSA) in which upper airway collapse is responsible for disrupted respiration. While central events are often seen in subjects with OSA, pure CSA is relatively rare.

OSA, however, is not a rare condition. It occurs in 2% to 4% of middle-aged adults and in 1% to 3% of preschool children. Overall it is estimated that there are 10 to 20 million sufferers in the U.S. However, despite the fact that apnea has such health and quality of life implications, there is a surprisingly low public and medical awareness of the illness. Of the 10 to 20 million sufferers in the U.S., it is estimated that only 10 to 15% have been diagnosed [2]. According to the World Health Organization approximately 100 million people worldwide have obstructive sleep apnea (OSA). In the United States, OSA is estimated to affect 1 in 4 men and 1 in 9 women; it also affects 23 million working adults. Approximately 4% of men and 2% of women over the age of 35 years have symptomatic moderate or severe OSA. It is estimated that less than 25% of OSA sufferers have been diagnosed[7].

Polysomnography (PSG) has become standard in diagnosing sleep disorders, including sleep apnea. PSG include recording of breath airflow, respiratory movement, oxygen saturation, electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG), as well as body position. PSG performed in the laboratory for a full night sleep under doctors and nurses supervision. Although PSG has been recognized as the golden standard for diagnosing sleep apnea, PSG got many criticisms from some researchers.

A PSG monitors several body functions during sleep and requires that the patient be hooked up to multiple probes (usually 16+) while staying overnight in a laboratory setting. It is widely agreed that PSG is a thorough and reliable test. However, it also receives its share of criticism. Firstly, PSG is inconvenient since it requires the patient to stay in hospital for one night. Secondly, it is an expensive process. This high cost is due to the need for the study to take place in a hospital setting, the requirement to have a sleep technician in attendance overnight, and the need to manually score the resultant measurements. Thirdly, many sleep centers worldwide are currently operating at full capacity and PSG usually suffers from a low availability reflected in up to 6 month-long waiting lists for testing. Hence, techniques which provide a reliable diagnosis of sleep apnoea with fewer and simpler measurements, and without the need for a specialized sleep laboratory may be of benefit[16].

Among all the PSG signals, ECG signal has been considered as one of the most extensively studied physiological signals. Electrocardiogram (ECG) is the interpretation of the electrical activity of the heart over a period of time, which is an effective low cost diagnostic tool for screening of cardiac abnormalities[4]. The ECG signal is a repetitive waveform that comprises several waves distinguished each other by frequencies and amplitudes. These waves originate from different parts of the heart and are denoted by letters P, QRS, T and U as shown in Figure 1.1.

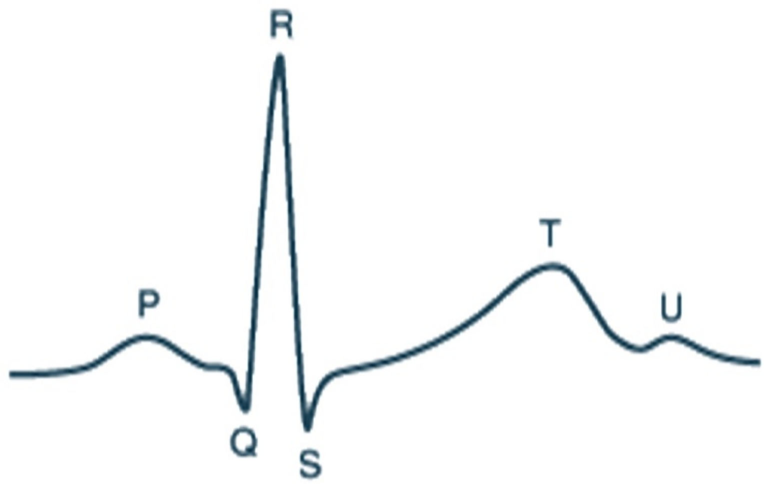

Figure 1.1: *ECG Signal*[4]

The RR intervals (R wave to R wave intervals), inverse of heart rate derived from ECG signals, are highly related to physiological manifestation of apnea events. The apnea/hypopnea elicits changes in both parasympathetic and sympathetic cardiac activities which cause the fluctuation of RR intervals. Episodes of OSA are accompanied by a characteristic heart rate pattern, known as cyclic variation of heart rate (CVHR), which consists of bradycardia during apnea followed by abrupt tachycardia on its cessation. Hence, the concealed information in ECG signals can be employed to detect the apnea/hypopnea events. In addition, with the fast development of advanced sensor technologies, the acquisition of ECG signals is quite convenient and reliable by remote biosensors and the derived RR intervals can be easily extracted from ECG signals by appropriate algorithms[4].

And because of the above reasons, Sleep Apnea is being undiagnosed in most of the cases. Therefore a need for simpler technology that has the same reliability with PSG that doesnt require special laboratory is long over due. And Hence, this project attempts to implement an Android based Sleep Apnea detecting system. The Figure 1.2 shows the basic block diagram of the proposed system.

Figure 1.2: *Basic Block Diagram*

1.1 Objective

The main goal of the project is to implement an independent Sleep Apnea detection system on an Android based platform. It includes,

- Detection of QRS complex from ECG signal
- Detection of R-R interval from the ECG signal
- Calculation Of Heart Rate.
- Extraction of Features.
- Detection of Sleep Apnea.

1.2 Motivation

The World Health Organization approximates that 100 million people worldwide have obstructive sleep apnea (OSA). Most of the people might be having sleep Apnea in their sleep. A sleep apnea episode of less than 4 per hour is considered as normal.

However, the danger with Sleep Apnea lies in the fact that the one suffering from sleep Apnea doesn't know about it or the severity of the condition. The time taken by the heart to recover from a single episode increases with increase in the number of apnea occurances. This might cause serious problems of the heart. Lack of low cost and easily available method for the detection of the condition seriously affects a person's life expectancy.

1.3 Scope

The fragmented sleep due to OSAS can result in poorer daytime cognitive performance, increased risk of motor vehicle and workplace accidents, depression, diminished sexual function, and memory loss. Undiagnosed OSAS is now regarded as an important risk factor for the development of cardiovascular diseases (e.g. hypertension, stroke, congestive heart failure, left ventricular hypertrophy, acute coronary syndromes). Therefore, early recognition of subjects at risk of OSAS is essential. However, Although PSG has been recognized as the golden standard for diagnosing sleep apnea, PSG got many criticisms from some researchers. This is due to several reasons, including uncomfortable, expensive, and limited availability. Therefore a need for simpler technology that has the same reliability with PSG that doesn't require special laboratory is long over due. This proposed project will provide the sufficient functionality to incorporate a low cost, comfortable and vastly available Android based system for diagnosing sleep apnea.

Chapter 2

LITERATURE REVIEW

In this chapter a detailed survey of each block of an Sleep Apnea detecting system from ECG is included.The system block are ECG preprocessing, QRS peak detection-R interval detection, Heart rate calculation, Sleep Apnea detection.

2.1 Sleep Apnea

Obstructive sleep apnoea syndrome (OSAS), commonly known as sleep apnea is defined by frequent cessation of breathing due to the partial or complete obstruction of upper airway for short periods during sleep. The fragmented sleep due to OSAS can result in poorer daytime cognitive performance, increased risk of motor vehicle and workplace accidents, depression, diminished sexual function, and memory loss. Undiagnosed OSAS is now regarded as an important risk factor for the development of cardiovascular diseases (e.g. hypertension, stroke, congestive heart failure, left ventricular hypertrophy, acute coronary syndromes)[10].

Based on the literature review, it was recognized that the events of apnea are accompanied by concomitant cyclic variations in R-R intervals (beat to beat heart rate) of ECG signals. The RR intervals (R wave to R wave intervals), inverse of heart rate derived from ECG signals, are highly related to physiological manifestation of apnea events. The apnea/hypoapnea elicits changes in both parasympathetic and sympathetic cardiac activities which cause the fluctuation of RR intervals. Episodes of OSA are accompanied by a characteristic heart rate pattern, known as cyclic variation of heart rate (CVHR), which consists of bradycardia during apnea followed by abrupt tachycardia on its cessation. Hence, the concealed information in ECG signals can be employed to detect the apnea/hypoapnea events. In addition, with the fast development of advanced sensor technologies, the acquisition of ECG signals is quite convenient and reliable by remote bio sensors and the derived RR intervals can be easily extracted from ECG signals by appropriate algorithms[4].

2.2 ECG Preprocessing

The preprocessing stage removes or suppresses noise from the raw ECG signal. ECG signal may be corrupted by various kinds of noises. The main noise sources are baseline wander, power line interference, muscle noise etc. The filtering techniques are primarily used for preprocessing of the signal and have as such been implemented in a wide variety of systems for ECG analysis. Considerable attention has been paid to the design of flters for the purpose of removing baseline wander and power line interference. Both types of disturbance imply the design of a narrow band filter.

Low frequency artifacts and baseline drift may be caused in the chest lead ECG signals by coughing or breathing, with large movements of the chest, or when an arm or leg is moved during the ECG data acquisition. Poor contact of the electrodes and perspiration of the patient under the electrodes may affect the electrode impedance which causes low frequency artifacts. Baseline drift may sometimes be caused by variations in temperature and bias in the instrumentation amplifiers as well. This type of noise is undesired and needs to be removed before any further signal processing, for proper analysis and display of the ECG signal. Removal of baseline wander is required in order to minimize changes in beat morphology that do not have cardiac origin, which is especially important when subtle changes in the low-frequency ST segment are analyzed for the diagnosis of ischemia, which may be observed, for example, during the course of a stress test. The frequency content of baseline wander is usually in the range below 0.5 Hz [19] .

2.3 QRS Complex Detection

The presence of a heartbeat and its occurrence time is the basic information required in all types of ECG signal processing. The QRS detection is an important and integral part of any sophisticated ECG signal processing system [17]. Several methods has been proposed for the extraction of QRS complex. Wavelet transform, Pan-Tomkins algorithm are some important among them [22]. Some of the QRS detection algorithm includes,

1. Wavelet Transform
2. Template Matching Technique
3. Pan Tompkins Algorithm

2.3.1 Wavelet Transform

The wavelet transform provides an appropriate basis for image handling because of its beneficial features. The assets of the wavelet transform are: The ability to compact most of the signals energy into a few transformation coefficients, which is called energy compaction. The ability to capture and represent effectively low frequency components(such as image backgrounds) as well as high frequency transients (such as image edges). The variable resolution decomposition with almost uncorrelated coefficients. The ability of a progressive transmission, which facilitates the reception of an image at different qualities.

A continuous wavelet transform (CWT) is used to divide a continuous-time function into wavelets. Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization[13]. In mathematics, the continuous wavelet transform of a continuous, square-integrable function x(t) at a scale a is greater than 0 and translational value b equal to R.

The mother wavelet used to generate all the basic functions is designed based on some desired characteristics associated with that function. The translation parameter relates to the location of wavelet function as it is shifted through the signal. Scaling either dilates or compress a signal.

2.3.2 Template Matching Technique

The idea behind this method is comparing the similarity between the incoming signal and a QRS template sequence. The basis for the method is the concept of correlation. The signals are said to be correlated if their wave shape matches or are similar. A measure of this is provided by correlation coefficient which is maximum when they are close. In the continuous correlation method of detecting QRS complex, a template of this morphology is cross correlated with the incoming signal. Here the template can be thought of as a window that moves over the incoming signal point-by-point. The algorithm begins by computing the cross correlation function and finding out the point when it is maximum. The point more or less represents the location of R wave of the incoming ECG and it is an indication of the occurrence of QRS complex.

2.3.3 Pan Tompkins Algorithm

Pan and Tompkins proposed a real time QRS detection algorithm based on analysis of the slope, amplitude and width of QRS complexes. The algorithm include low pass, high pass, derivative, squaring, moving window integration and thresholding stage [17].

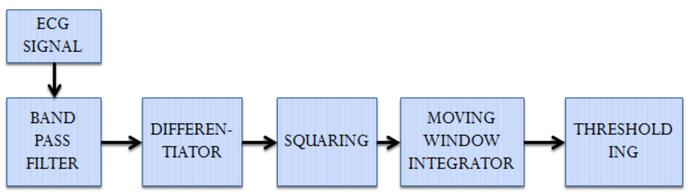

Figure 2.1: *Pan Tompkins Algorithm*[17]

1. Band Pass Filter

In order to attenuate the noise, the signal should be passed through a digital band pass filter. The band pass filter reduces the influence of muscle noise, baseline wander, and T-wave interference. Preprocessing the ECG with this digital band pass filter improves the signal to noise ratio. The pass band that maximizes the QRS energy is approximately in the 5-15 Hz range. A low pass and a high pass filter are cascaded to form band pass filter.

2. Differentiator

   The next process after filtering is differentiation. The differentiation is a standard technique for finding the high slopes that normally distinguish the QRS complex from other ECG. Thus information about slope of QRS complex is obtained in the derivative stage.

3. Squaring Function

   After differentiation, the signal is squared. That is all signal samples are squared point-by-point. This operation makes all data points in the processed signal positive, and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the ECG signal, which are mainly due to the QRS complex and restricts false positive caused by T waves.

4. Moving Window Integration

   The slope of R wave alone is not a guaranteed way to detect a QRS event. Many abnormal QRS complexes that have large amplitudes and long durations might not be detected using information about of slope of R wave only. Thus for detecting QRS event more information has to be extracted. The purpose of moving-window integration is to obtain waveform feature information in addition to the slope of the R wave.

5. Thresholding

   In this the output of the moving window integrator need to be compared with a certain threshold value. QRS complexes are detected in regions where the filtered signal rises above the threshold. Thus with the help of Pan-Tompkins algorithm the information about slope, amplitude and width of QRS complexes are obtained. The main advantage of this algorithm is its high accuracy in terms of QRS detection and its speed of operation.

2.4 R-R Interval Detection

The peak of the QRS complex corresponds to R-wave. Thus the R-wave of each cardiac cycle are detected. By measuring the time interval between the adjacent R peaks, R-R interval can be estimated.

2.5 Feature Extraction

The events of apnea are accompanied by concomitant cyclic variations in R-R intervals (beat to beat heart rate) of ECG signals. The RR intervals (R wave to R wave intervals), inverse of heart rate derived from ECG signals, are highly related to physiological manifestation of apnea events. Technique relies on an effective combination of ECG signal features. The following ECG features were found to be most effective for apnea detection [10][4][25]:

- Mean epoch and recording RR-interval.
- Standard deviation of the epoch and recording RR interval.
- The NN50 measure (variant 1), defined as the number of pairs of adjacent RR intervals where the first RR interval exceeds the second RR interval by more than 50 ms.
- The NN50 measure (variant 2), defined as the number of pairs of adjacent RR intervals where the second RR interval exceeds the first RR interval by more than 50 ms.
- Two pNN50 measures, defined as each NN50 measure divided by the total number of RR-intervals.

- The SDSD measures, defined as the standard deviation of the differences between adjacent RR intervals.
- The RMSSD measures, defined as the square root of the mean of the sum of the squares of differences between adjacent RR intervals.
- Median of RR-intervals.
- Inter-quartile range, defined as difference between 75th and 25th percentiles of the RR-interval value distribution.
- Mean absolute deviation values, defined as mean of absolute values obtained by the subtraction of the mean RR-interval values from all the RR-interval values in an epoch.

2.6 Apnea Hypopnea Index

The ApneaHypopnea Index or ApnoeaHypopnoea Index (AHI) is an index used to indicate the severity of sleep apnea. It is represented by the number of apnea and Hypopnea events per hour of sleep. The AHI is calculated by dividing the number of apnea events by the number of hours of sleep [26]. AHI values are categorized as:

- Normal: 0-4
- Mild Sleep Apnea: 5-14
- Moderate Sleep Apnea: 15-29
- Severe Sleep Apnea: 30 or more

Chapter 3

ANDROID

Android is an operating system (OS) based on the Linux kernel and currently developed by Google, With a user interface based on direct manipulation. Android is used because of its open nature, widespread use and portability of the code.The software framework consists of three components. A data delivery service that provide data streaming, signal processing service with above mentioned algorithms and a graphical user interface that displays the results. Further more, as Android is a common platform now a days, development of a system would greatly reduce many disadvantages as it is available with almost all individual.

3.1 Android Architecture

Android operating system is a stack of software components which is roughly divided into five sections and four main layers as shown below in the architecture diagram.

3.1.1 Linux Kernel

At the bottom of the layers is Linux with approximately 115 patches. This provides basic system functionality like process management, memory management, device management like camera, keypad, display etc. Also, the kernel handles all the things that Linux is really good at such as networking and a vast array of device drivers, which take the pain out of interfacing to

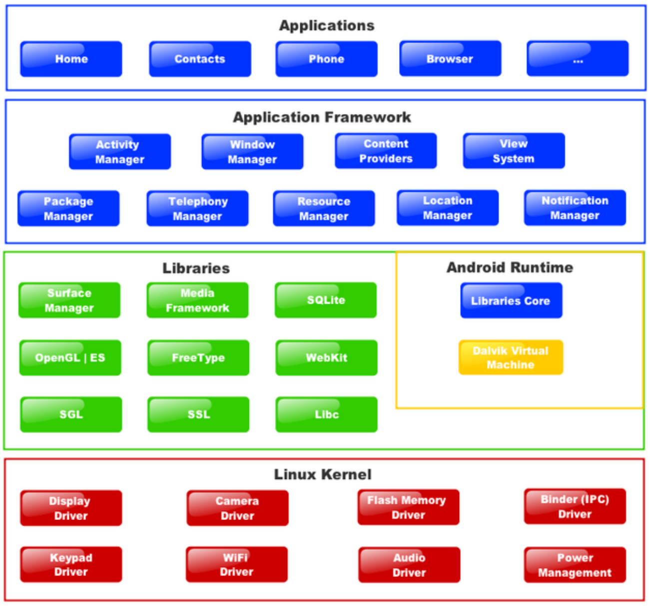

Figure 3.1: *Android Architecture*

peripheral hardware.

3.1.2 Libraries

On top of Linux kernel there is a set of libraries including open-source Web browser engine WebKit, well known library libc, SQLite database which is a useful repository for storage and sharing of application data, libraries to play and record audio and video, SSL libraries responsible for Internet security etc..

3.1.3 Android Run Time

This is the third section of the architecture and available on the second layer from the bottom. This section provides a key component called Dalvik Virtual Machine which is a kind of Java Virtual Machine specially designed and optimized for Android. The Dalvik VM makes use of Linux core features like memory management and multi-threading, which is intrinsic in the Java language. The Dalvik VM enables every Android application to run in its own process, with its own instance of the Dalvik virtual machine. The Android runtime also provides a set of core libraries which enable Android application developers to write Android applications using standard Java programming language. Dalvik is open-source software. Dan Bornstein, who named it after the fishing village of Dalvik in Eyjaforer, Iceland, where some of his ancestors lived, originally wrote Dalvik VM. It is the software responsible for running apps on Android devices.

3.1.4 Application Framework

The Application Framework layer provides many higher-level services to applications in the form of Java classes. Application developers are allowed to make use of these services in their applications.

3.1.5 Application

You will find all the Android application at the top layer. You will write your application to be installed on this layer only. Examples of such applications are Contacts Books, Browser, Games etc.

3.1.6 Android Canvas

The Canvas class holds the "draw" calls. To draw something, you need 4 basic components: A Bitmap to hold the pixels, a Canvas to host the draw calls (writing into the bitmap), a drawing primitive (e.g. Rect, Path, text, Bitmap), and a paint (to describe the colors and styles for the drawing).

The Android framework APIs provides a set of 2D-drawing APIs that allow you to render your own custom graphics onto a canvas or to modify existing Views to customize their look and feel. When drawing 2D graphics, you'll typically do so in one of two ways:

- Draw your graphics or animations into a View object from your layout. In this manner, the drawing of your graphics is handled by the system's normal View hierarchy drawing process you simply define the graphics to go inside the View.

- Draw your graphics directly to a Canvas. This way, you personally call the appropriate class's onDraw() method (passing it your Canvas), or one of the Canvas draw...() methods (like drawPicture()). In doing so, you are also in control of any animation.

3.1.7 Proposed Work

The aim of the project is to implement an Android Based Sleep Apnea Detector for identifying Sleep Apnea from ECG signal during sleep. The primary purpose is to monitor patients cardiac activity to understand and deduce any occurrence of sleep apnea.

Chapter 4

SYSTEM OVERVIEW

The aim of the project is to implement an Android Based Sleep Apnea Detector for identifying Sleep Apnea from ECG signal during sleep. The block diagram of proposed system is shown below.

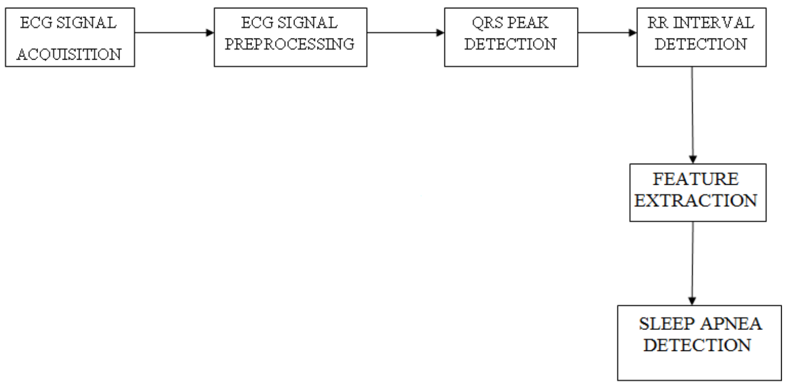

Figure 4.1: *Block Diagram*

The primary purpose is to monitor patients cardiac activity to understand and deduce any occurrence of sleep apnea. The ECG signal taken from the patient body are processed for determining different Apnea features. The ECG signal taken from the patient body usually have a very low amplitude and contains a lot of artifacts caused by muscle contraction, respiration, movement of electrode cables etc. So it is important to process ECG signals for further analysis and interpretations. The whole processing of ECG signals is done in Android.Different steps in processing of ECG signal includes preprocessing, feature extraction, Sleep Apnea detection and calculating the Apnea Hypopnea Index for classifying the patient.

4.1 ECG signal acquisition

The Physionet data base is used as the input to the system.The data consist of 70 records, divided into a learning set of 35 records and a test set of 35 records, all of which may be downloaded. Recordings vary in length from slightly less than 7 hours to nearly 10 hours each. Each recording includes a continuous digitized ECG signal, a set of apnea annotations (derived by human experts on the basis of simultaneously recorded respiration and related signals), and a set of machine-generated QRS annotations (in which all beats regardless of type have been labeled normal).

4.2 ECG signal preprocessing

This stage removes or suppresses the noise from the ECG signal. The main noise that may affect ECG signal includes patient-electrode motion artifacts, EMG noise (Electromyographic noise) caused by muscle movement, baseline wandering etc.This noise signals usually corrupts the signals. Prior to analysis of the signal pre-processing is necessary to remove the noise. Eliminating the baseline wandering and power line interference are usually the necessary pre-processing steps to enhance signal characteristics for diagnosis. Preprocessing can be done by using a digital filter approach. The signal also has to be normalised before QRS detection.

4.3 QRS peak detection

For QRS peak detection Pan-Tompkin algorithm is used. There are other algorithms for ECG analysis but the Pan and Tompkins algorithm was found to be better for the current situation. Pan and Tompkins algorithm is based on analysis of the slope, amplitude and width of QRS complexes. The algorithm include low pass filter, high pass filter, derivative filter, squaring, moving window integration and thresholding stage [17].

1. Low Pass Filter

   Low-pass filter can reduce powerline noise because it can supress high frequency noise. The transfer function of the second-order low-pass filter is given by,

   $$H(z) = \frac{(1 - Z^{-6})^2}{(1 - Z^{-1})^2} \tag{4.1}$$

   where the cutoff frequency is about 11 Hz and the gain is 36 [17].

2. High Pass Filter

   High-pass filter can reduce baseline noise. The design of the high-pass filter is based on subtracting the output of a first-order low-pass filter from an all-pass filter (i.e.,the samples in the original signal). The transfer function for such a high-pass filter is,

   $$H(Z) = \frac{(-1 + 32Z^{-16} + Z^{-32})}{(1 + Z^{-1})} \tag{4.2}$$

   The low cutoff frequency of this filter is about 5 Hz, the gain is 32 [17].

3. Differentiator

   The next process after filtering is differentiation. The differentiation is a standard technique for finding the high slopes that normally distinguish the QRS complex from other ECG. Thus information about slope of QRS complex is obtained in the derivative stage. The transfer function for the differentiator is given by,

   $$H(Z) = (1/8T)(-Z^{-2} - 2Z^{-1} + 2Z^{1} + Z^{2}) \tag{4.3}$$

4. Squaring Function

   After differentiation, the signal is squared. That is all signal samples are squared point-by-point. This operation makes all data points in the processed signal positive, and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the ECG signal, which are mainly due to the QRS complex and restricts false positive caused by T waves. This can be given as,

$$y(nT) = [x(nt)]^2 \tag{4.4}$$

5. Moving Window Integration

   The slope of R wave alone is not a guaranteed way to detect a QRS event. Many abnormal QRS complexes that have large amplitudes and long durations might not be detected using information about of slope of R wave only. Thus for detecting QRS event more information has to be extracted. The purpose of moving-window integration is to obtain waveform feature information in addition to the slope of the R wave.

$$y(nT) = (1/N)[x(nT-(N-1)T)+x(nT-(N-2)T)+***+x(nT)] \tag{4.5}$$

6. Thresholding

   In this the output of the moving window integrator need to be compared with a certain threshold value. QRS complexes are detected in regions where the filtered signal rises above the threshold. Thus with the help of Pan-Tompkins algorithm the information about slope, amplitude and width of QRS complexes are obtained. The main advantage of this algorithm is its high accuracy in terms of QRS detection and its speed of operation.

4.4 R-R interval detection

During certain sleep disorder conditions, variation of R-R interval will occur.By measuring the time interval between the adjacent R peaks, R-R interval can be estimated. The R-R interval can be estimated as,

$$H(Z) = \frac{TotalTime}{TotalSamples} * SamplesBetweenPeaks. \tag{4.6}$$

4.5 Feature Extraction

The Features explained in the Literature review is calculated from the RR interval and these features are used to detect a Sleep Apnea episode. The features that are measured in this particular implementations include:

1. R R Interval
2. Epoch length
3. The NN50 measure (variant 1), defined as the number of pairs of adjacent RR intervals where the first RR interval exceeds the second RR interval by more than 50 ms.
4. The NN50 measure (variant 2), defined as the number of pairs of adjacent RR intervals where the second RR interval exceeds the first RR interval by more than 50 ms.

The above feature will be calculated and used to detect each apnea event.

4.6 Apnea Classification

Now, after the apnea events are detected, we calculate the Apnea-Hypopnea Index. The ApneaHypopnea Index or ApnoeaHypopnoea Index (AHI) is an index used to indicate the severity of sleep apnea. It is represented by the number of apnea and Hypopnea events per hour of sleep. The

AHI is calculated by dividing the number of apnea events by the number of hours of sleep. Using The AHI, the sleep can be classified as,

- Normal.
- Mild Sleep Apnea.
- Moderate Sleep Apnea.
- Severe Sleep Apnea.

Chapter 5

REQUIREMENT ANALYSIS

The Requirements of the project includes Octave for the simulation, and tools like Android SDK, ADT plugin, Android Emulator, Android Debug bridge, JRE and the ECG database.

5.1 Octave

GNU Octave is a high-level interpreted language, primarily intended for numerical computations. It provides capabilities for the numerical solution of linear and nonlinear problems, and for performing other numerical experiments. It also provides extensive graphics capabilities for data visualization and manipulation. Octave is normally used through its interactive command line interface, but it can also be used to write non-interactive programs. The Octave language is quite similar to Matlab so that most programs are easily portable. Qt-Octave is a front-end for Octave.

One of its greatest strengths is that Octave allows building its own reusable tools. Customized special functions and programs can be easily created in the Octave code. Bio medical engineers use Octave in research,design, and manufacturing of medical devices and to develop embedded algorithms and systems for medical instrumentation. Octave has several advantages over other traditional means of numerical computing.

- It allows quick and easy coding in a high level language.

- An interactive interface allows rapid experimentation and easy debugging.
- Data structures require minimal attention, in particular, arrays need not be declared before first use.
- High quality graphic and visualization facilities are available.
- Octave M-files are completely portable across a wide range of platforms

5.2 Android SDK

The Android SDK provides you the API libraries and developer tools necessary to build, test, and debug apps for Android. Download the ADT Bundle to quickly start developing apps. It includes the essential Android SDK components and a version of the Eclipse IDE with built-in ADT (Android Developer Tools) to streamline your Android app development. With a single download, the ADT Bundle includes everything you need to begin developing apps:

1. Eclipse and ADT plugin.
2. Android SDK Tools
3. The latest Android platform.
4. The latest Android system image for the emulator

The Android software development kit (SDK) includes a comprehensive set of development tools. These includes debugger, libraries, a handset emulator based on QEMU, documentation, sample code, and tutorials. Currently supported development platforms includes computers running Linux (any modern desktop Linux distribution), Mac OS X 10.5.8 or later,Windows XP or later; for the moment one can develop Android software on Android itself by using AIDE [Android IDE - Java] app and Android java editor app. The officially supported integrated development environment (IDE) is

Eclipse. Android Development Tools (ADT) Plugin fully supports Android development out of the box.

Net Beans IDE also supports Android development via a plug-in. Additionally, developers may use any text editor to edit Java and XML files, then use command line tools (Java Development Kit and Apache Ant are required) to create, build and debug Android applications as well as control attached Android devices (e.g., triggering a reboot, installing software package(s) remotely).

5.3 ADT Plugin

Android Development Tools (ADT) is a plugin for the Eclipse IDE that is designed to give you a powerful, integrated environment in which to build Android applications. ADT extends the capabilities of Eclipse to set up new Android projects, create an application GUI, add packages based on the Android Framework API, debug your applications using the Android SDK tools, and even export signed (or unsigned) .apk files in order to distribute application.

In addition to Eclipse's standard editor features, ADT provides custom XML editors to help you create and edit Android manifests, resources, menus, and layouts in a form-based or graphical mode. Double-clicking on an XML file in Eclipse's package explorer opens the appropriate XML editor. In addition, some special file types that don't have custom editors, such as drawables, animations, and color files offer editing enhancements such as XML tag completion.

5.4 Android Emulator

The Android SDK includes a mobile device emulator a virtual mobile device that runs on your computer. The emulator lets you develop and test Android applications without using a physical device. Android applications are packaged in .apk format and stored under /data/app folder on the Android OS (the folder is accessible only to the root user for security reasons).

APK package contains .dex files (compiled byte code files called Dalvik executables), resource files, etc.

The Android emulator mimics all of the hardware and software features of a typical mobile device, except that it cannot place actual phone calls. It provides a variety of navigation and control keys, which you can "press" using your mouse or keyboard to generate events for your application. It also provides a screen in which your application is displayed, together with any other active Android applications.

5.5 Android Debug Bridge

The Android Debug Bridge (ADB) is a tool kit included in the Android SDK package. It consists of both client and server-side programs that communicate with one another. The ADB is typically accessed through the command-line interface, although numerous graphical user interfaces exist to control ADB. It includes three components:

- A client, which runs on your development machine. You can invoke a client from a shell by issuing an adb command. Other Android tools such as the ADT plugin and DDMS also create adb clients.
- A server, which runs as a background process on your development machine. The server manages communication between the client and the adb daemon running on an emulator or device.
- A daemon, which runs as a background process on each emulator or device instance.

5.6 JRE

The Java Runtime Environment (JRE) provides the libraries, the Java Virtual Machine, and other components to run applets and applications written in the Java programming language. In addition, two key deployment technologies are part of the JRE: Java Plug-in, which enables applets to run in popular browsers; and Java Web Start, which deploys standalone applications over a network.

5.7 Database

The Physionet data base is used as the input to the system.The data consist of 70 records, divided into a learning set of 35 records and a test set of 35 records, all of which may be downloaded. Recordings vary in length from slightly less than 7 hours to nearly 10 hours each. Each recording includes a continuous digitized ECG signal, a set of apnea annotations (derived by human experts on the basis of simultaneously recorded respiration and related signals), and a set of machine-generated QRS annotations (in which all beats regardless of type have been labeled normal).

Chapter 6

IMPLEMENTATION AND RESULTS

The Physio-net Sleep Apnea ECG database was obtained and Octave simulation was done, with the intention of extracting sleep apnea event from the data. The data consist of 70 records, divided into a learning set of 35 records and a test set of 35 records. Recordings vary in length from slightly less than 7 hours to nearly 10 hours each. Below shows the results of different stages of the simulation.

6.1 Octave Simulation

In this stage the Physio-net Sleep Apnea ECG database was obtained and loaded to octave. The different signal processing steps and algorithms are done on this obtained database. The database is of 1 hour in length and has a sampling rate of 100 samples per second.

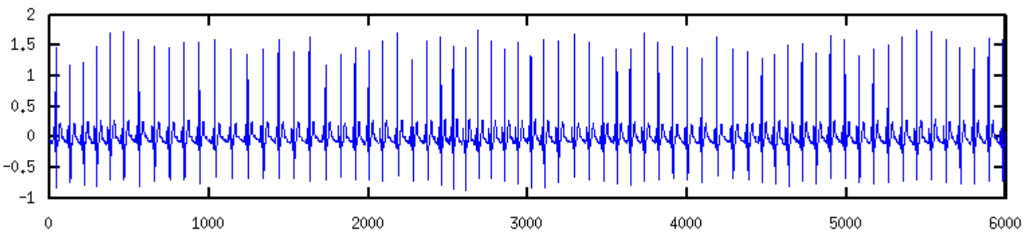

Figure 6.1: *Input ECG Signal*

6.1.1 ECG Signal Preprocessing

This stage removes or suppresses the noise from the ECG signal. The main noise that may affect ECG signal includes patient-electrode motion artifacts, EMG noise (Electromyographic noise) caused by muscle movement, baseline wandering etc. Also, the database had a sampling rate of 100 samples per second, this was up-sampled to 200 samples per second.

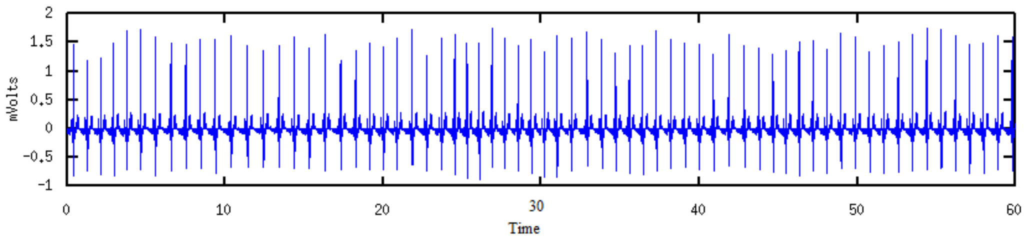

Figure 6.2: *Up-sampled ECG Signal*

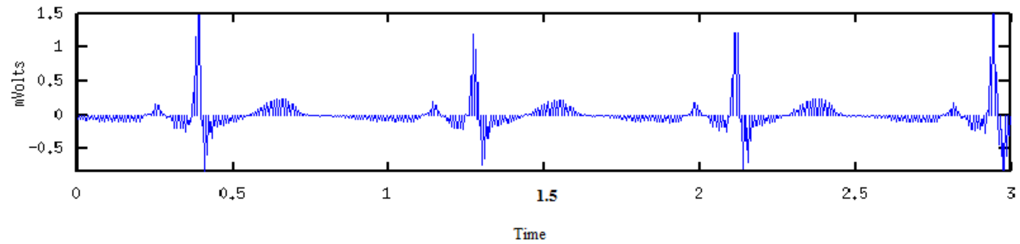

Figure 6.3: *Up-sampled ECG Signal(3 sec)*

6.1.2 Pan Tompkins Algorithm

For QRS peak detection Pan-Tompkin algorithm is used.Pan and Tompkins algorithm is based on analysis of the slope, amplitude and width of QRS complexes. The algorithm include low pass, high pass, derivative, squaring, moving window integration and thresholding stage.

Low Pass Filter

Low-pass filter can reduce powerline noise because it can supress high frequency noise.The output of the lowpass filter is shown below in figures 6.4 and 6.5.

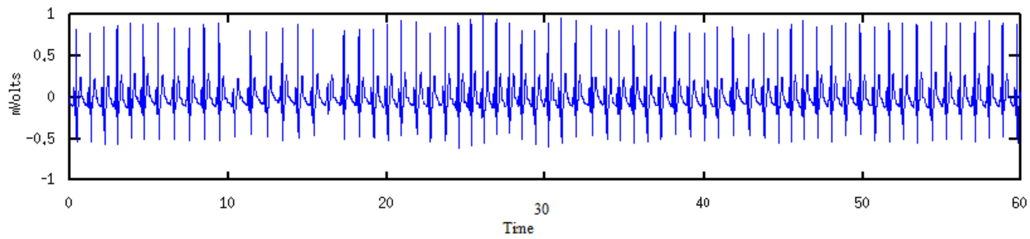

Figure 6.4: *ECG Signal after LPF*

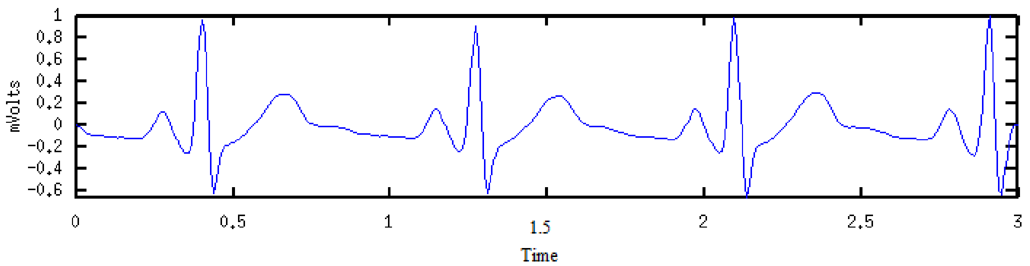

Figure 6.5: *ECG Signal after LPF (3 sec)*

High Pass Filter

High-pass filter can reduce baseline noise.The output of the high pass filter is shown in figure 6.6 and 6.7.

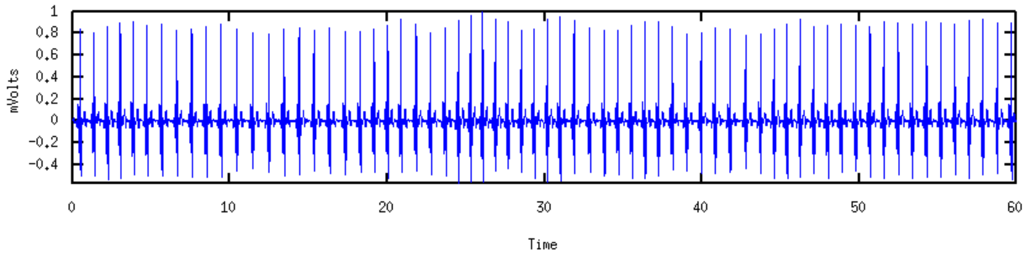

Figure 6.6: *ECG Signal after HPF*

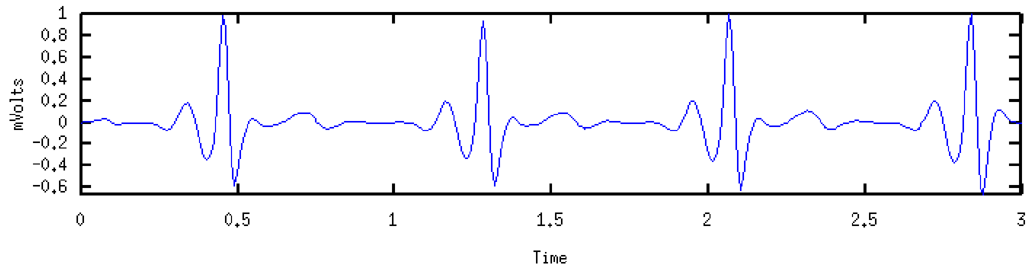

Figure 6.7: *ECG Signal after HPF (3 sec)*

Derivative filter

The next process after filtering is differentiation. The differentiation is a standard technique for finding the high slopes that normally distinguish the QRS complex from other ECG. Thus information about slope of QRS complex is obtained in the derivative stage It is shown in Figure 6.8 and 6.9.

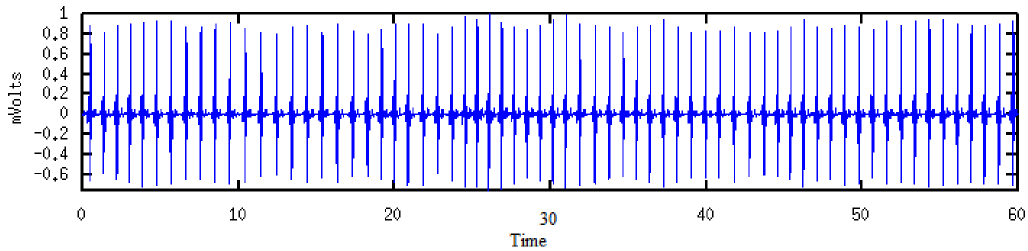

Figure 6.8: *ECG Signal after Derivative*

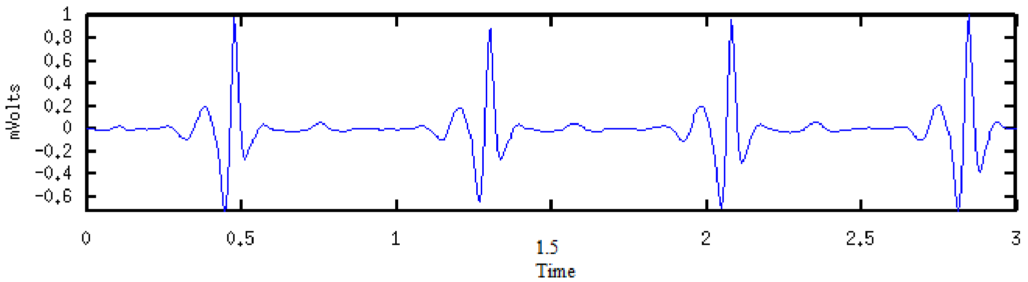

Figure 6.9: *ECG Signal after Derivative (3 sec)*

Squaring

After differentiation, the signal is squared. That is all signal samples are squared point-by-point. This operation makes all data points in the processed signal positive, and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the ECG signal, which are mainly due to the QRS complex and restricts false positive caused by T waves. It is shown in Figure 6.10 and 6.11.

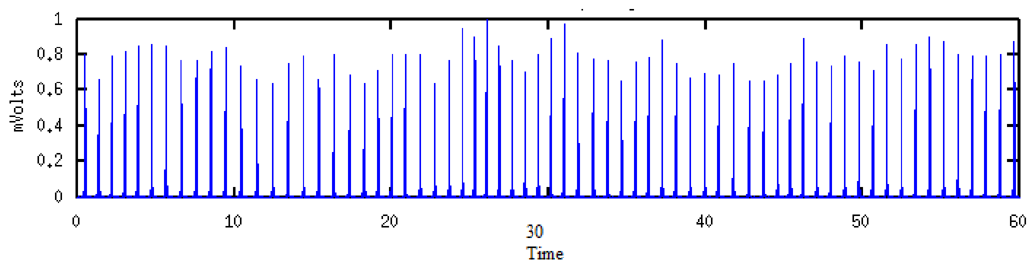

Figure 6.10: *ECG Signal after Squaring*

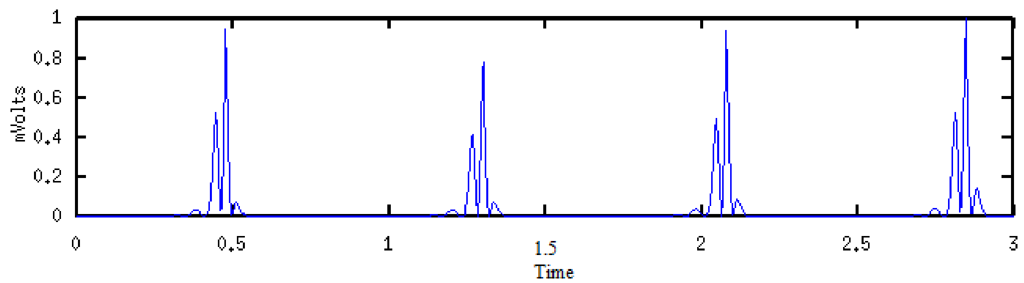

Figure 6.11: *ECG Signal after Squaring (3 sec)*

Moving Average Filter

The slope of R wave alone is not a guaranteed way to detect a QRS event. Many abnormal QRS complexes that have large amplitudes and long durations might not be detected using information about of slope of R wave only. Thus for detecting QRS event more information has to be extracted. The purpose of moving Average Filter is to obtain waveform feature information in addition to the slope of the R wave. It is shown in figure 6.12 and 6.13.

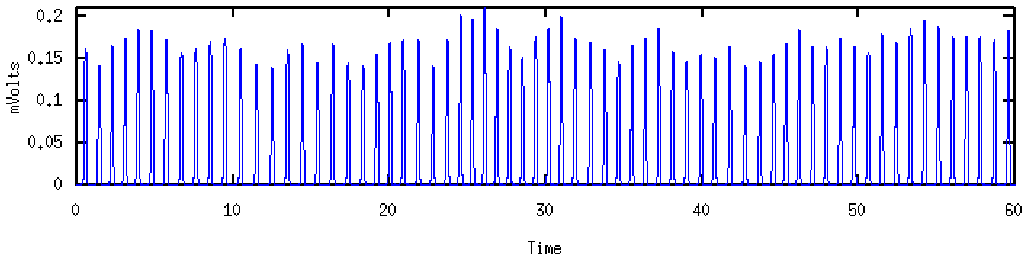

Figure 6.12: *ECG Signal after Moving Average Filter*

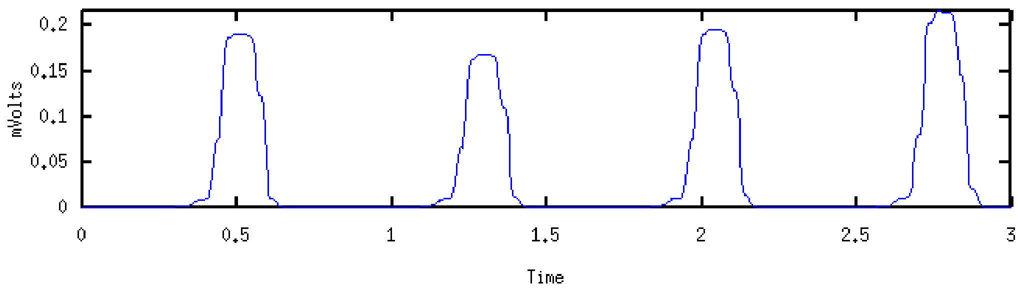

Figure 6.13: *ECG Signal after Moving Average Filter (3 sec)*

6.1.3 Thresholding/R Peak Detection

In this the output of the moving window integrator need to be compared with a certain threshold value. QRS complexes are detected in regions where the filtered signal rises above the threshold. Thus with the help of Pan-Tompkins algorithm the information about slope, amplitude and width of QRS complexes are obtained. It is shown in figure 6.14 and 6.15

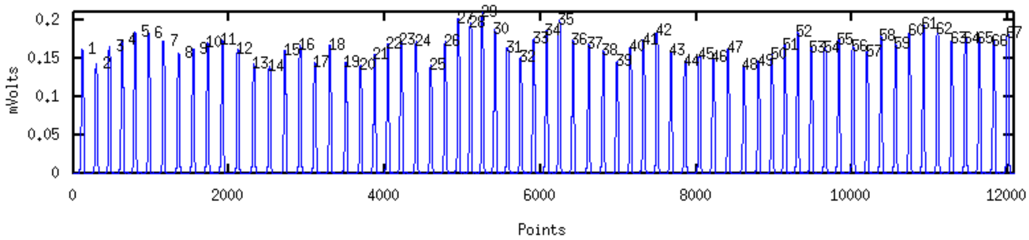

Figure 6.14: *ECG Signal after R Peak Detection*

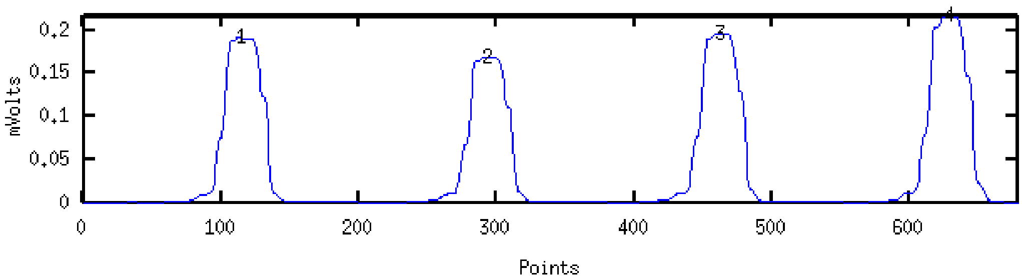

Figure 6.15: *ECG Signal after R Peak Detection (3 sec)*

6.1.4 R-R Interval Detection

The peak of the QRS complex corresponds to R-wave. Thus the R-wave of each cardiac cycle are detected. By measuring the time interval between the adjacent R peaks, R-R interval can be estimated. it is shown in figure 6.16.

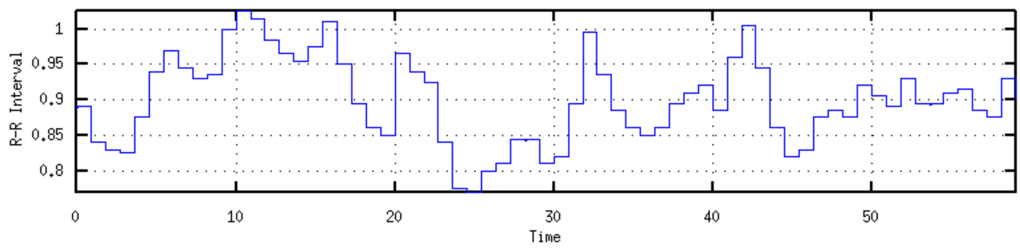

Figure 6.16: *R-R Interval Graph*

6.1.5 Heart Rate Detection

From the detected R-R interval the heart rate can be measured by using the formula,

$$HeartRate = \frac{(SamplingRate)}{(RRInterval)} * 60.$$

It is shown in figure 6.17.

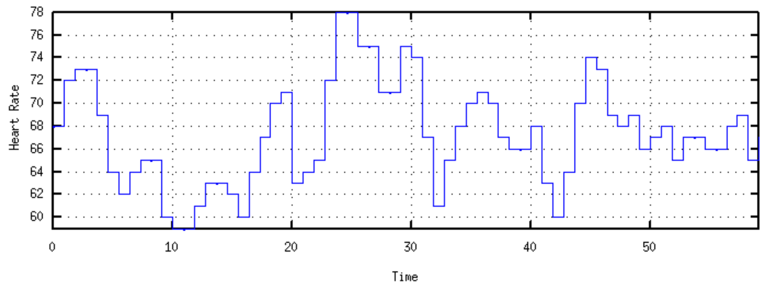

Figure 6.17: *Heart Rate*

6.1.6 Averaged R-R Interval And Heart Rate

The above R-R interval and Heart rate was calculated from the individual R-R intervals. However this shows large variations in consecutive values and hence we go for the average RR interval and the subsequent Heart rate. The new R-R interval was calculated by averaging the 4 consecutive R-R interval and a new Heart rate was derived from this. The new values shows much less variations. And this makes it easier to detect apnea events. It is shown in figure 6.18 and 6.19.

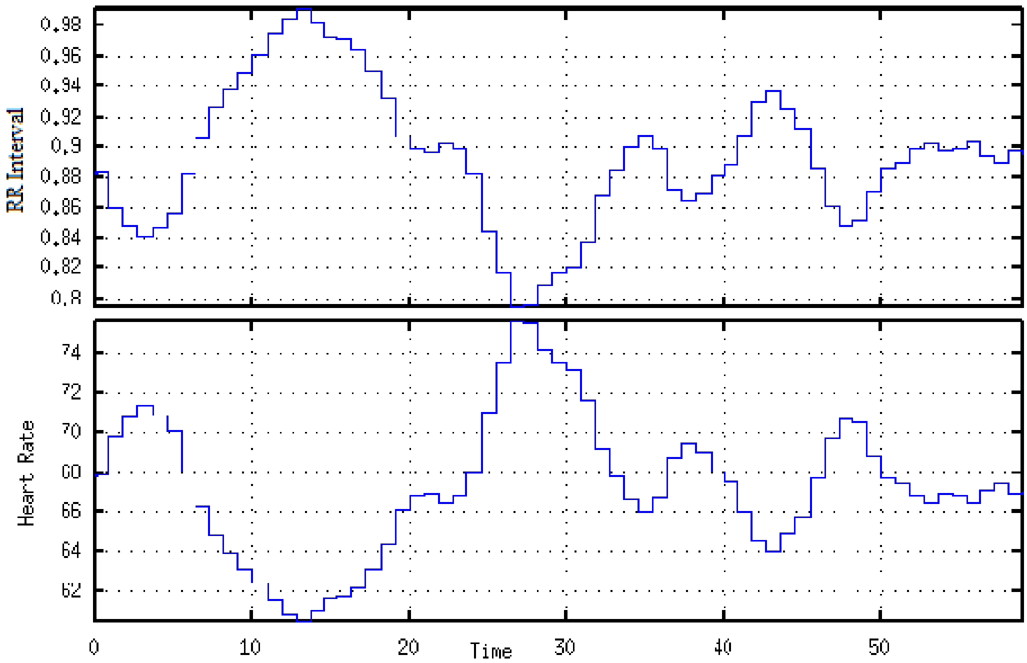

Figure 6.18: *Averaged RR interval and Heart Rate(60 sec)*

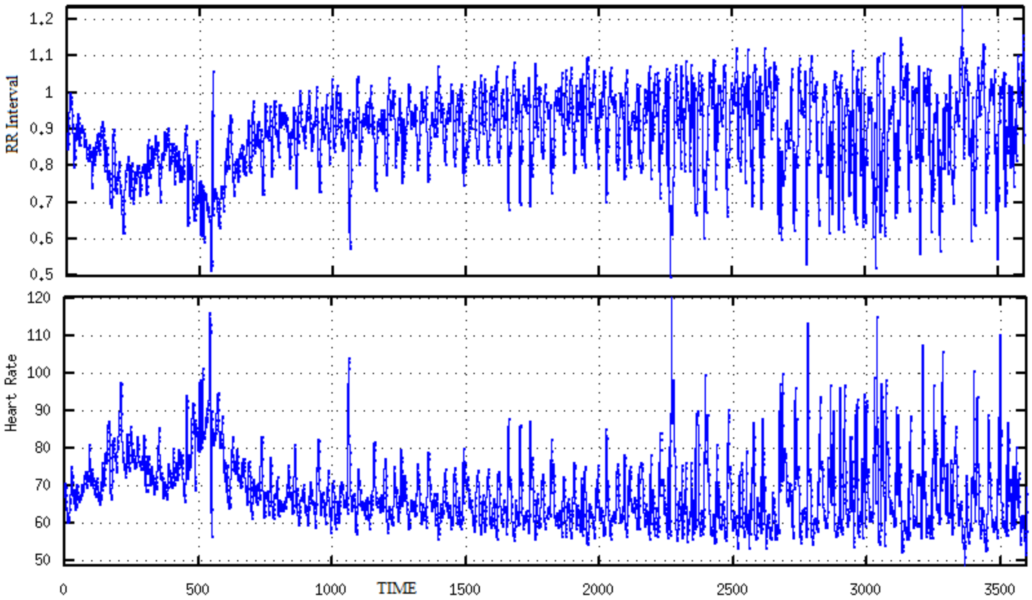

Figure 6.19: *Averaged RR interval and Heart Rate(Apnea)(1 hour)*

The figure 6.20 shows the R-R interval and the Heart rate of the normal ECG database. We can learn, by comparing the case of normal and Apnea database, that the Apnea database shows a significant variation in the R-R interval than the normal database. In case of the normal database, the R-R interval is mostly concentrated on a particular range of values (except in case of Arrhythmia cases), near 0.8 sec in this particular case. Thus we can conclude that, the Sleep Apnea can be detected from ECG.

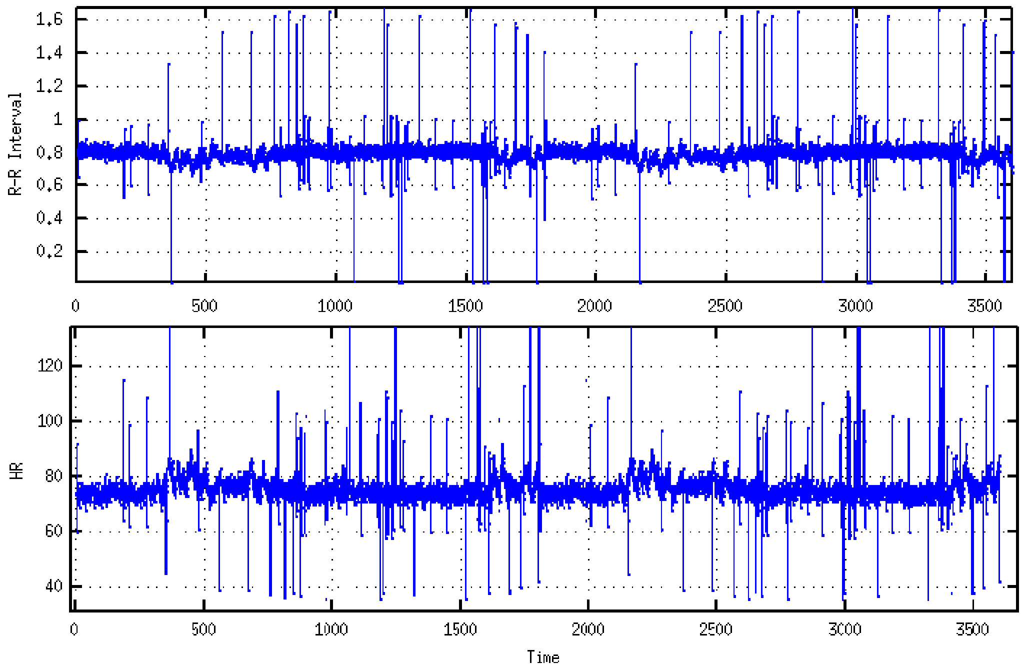

Figure 6.20: *Averaged RR interval and Heart Rate(Normal)(1 hour)*

6.1.7 Apnea Episode Detection

Now, that the RR Interval and the Heart rate has been calculated, we can calculate the other features for determining the sleep Apnea condition. After calculating the rest of features, the apnea episodes were detected. After careful experimentation the epoch length was set to be 8 sec in both directions of the RR interval in consideration. The NN50 variant measure was set as 60 ms instead of 50 ms as it improved the accuracy of the system. The Apnea detection is shown in figures 6.21 and 6.22.

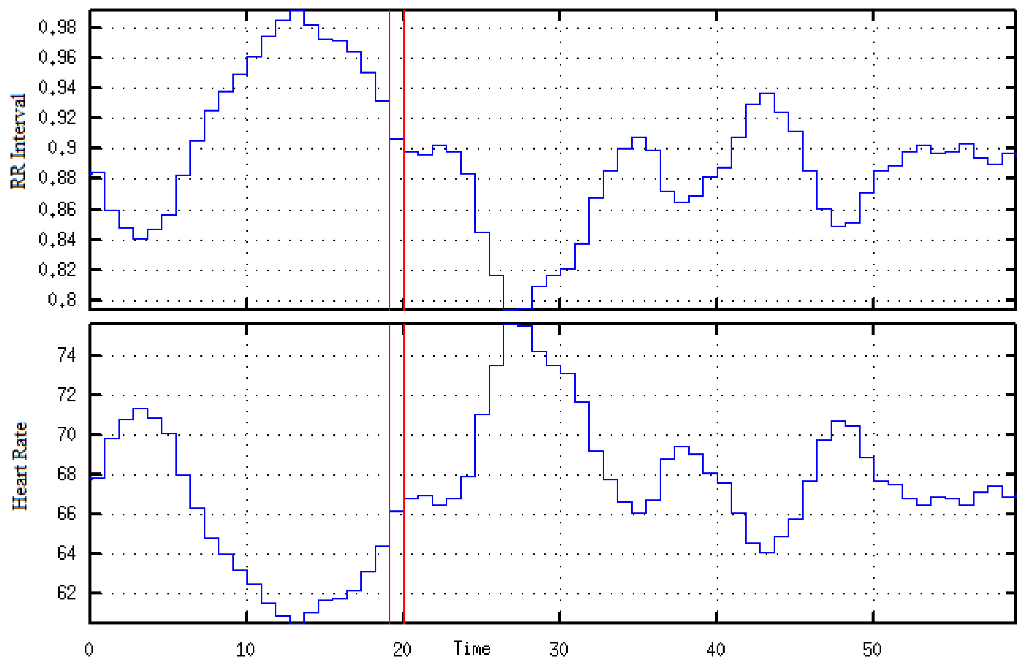

Figure 6.21: *Apnea Episodes(60 seconds)*

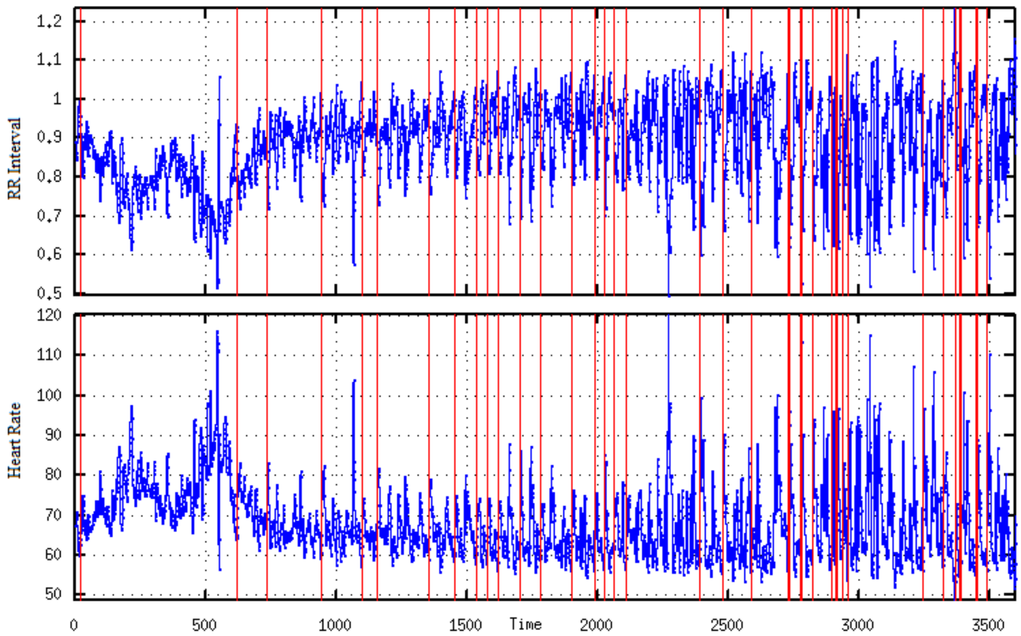

Figure 6.22: *Apnea Episodes(1 hour)*

6.1.8 Apnea Classification

For classifying a particular database according to the severity of the apnea, the Apnea-Hypopnea Index was estimated from the above features. And according to the AHI, the data base was classifies as Normal, Mild, Moderate and Severe. An example is shown in figure 6.23.

```
No_Of_Apnea_Episode =  39
hours =  1
AHI =  39
Severe Sleep Apnea Detected
```

Figure 6.23: *Apnea Classified*

6.2 Octave Simulation Results

During the previous section of the work, 115 hours of ECG data from the Physionet Sleeep Apnea ECG data base was tested. The following results were obtained.

Table 6.1: ***Simulation Results***

Epoch	RR Diff.	NN50	Apnea	Detected	Accuracy
5 sec	50 ms	4 No's	4493 No's	2503 No's	55.71%
5 sec	55 ms	4 No's	4493 No's	2564 No's	57.07%
5 sec	60 ms	4 No's	4493 No's	2741 No's	61.01%
6 sec	50 ms	4 No's	4493 No's	2516 No's	56.00%
6 sec	55 ms	5 No's	4493 No's	2806 No's	62.45%
6 sec	60 ms	6 No's	4493 No's	2887 No's	64.25%
7 sec	50 ms	4 No's	4493 No's	2741 No's	61.01%
7 sec	55 ms	5 No's	4493 No's	3016 No's	67.12%
7 sec	60 ms	6 No's	4493 No's	3170 No's	70.56%
8 sec	50 ms	5 No's	4493 No's	3120 No's	69.44%
8 sec	55 ms	5 No's	4493 No's	3192 No's	71.05%
8 sec	60 ms	5 No's	4493 No's	3251 No's	72.35%
8 sec	60 ms	6 No's	4493 No's	3367 No's	74.93%
9 sec	60 ms	5 No's	4493 No's	3195 No's	71.11%
9 sec	60 ms	6 No's	4493 No's	3277 No's	72.94%
10 sec	60 ms	6 No's	4493 No's	3152 No's	70.16%

Based on the simulation it was noted that the maximum accuracy was obtained when the epoch length was 8 sec, The difference in RR interval was 60 ms and the NN50 values (variants 1 and 2) equal to 6. However, there was a significant number of undetected QRS complexes. The maximum accuracy obtained was 74.93 %. 5 hours of normal ECG database was tested and 0 Apnea episodes were detected with an accuracy of 100%. However, it was noted that, when multiple Tachycardia or Bradycardia or a combination of these occur, it was detected as a sleep apnea episode.

6.3 Android Implementation

The Pan-Tompkins algorithm was coded in java and implemented in Android for the extraction of different features for the detection of sleep Apnea. The application, reads the ECG data from the database. Then the data undergoes preprocessing. This stage removes or suppresses the noise from the ECG signal.

Then, the preprocessed data is compared with a threshold to detect the peaks. The no of samples between each peaks gives the RR-interval and Heart Rate along with other Apnea features. From these measured features Apnea is classified.Unlike in the simulation stage, the data was scaled to a range of 0 to 1, so that the peak detection and the extraction of features become more accurate. For this the data was given a positive shift, so that every data sample lies in the positive region. The the data was divided with the maximum value so that the range of the data lies in between 0 and 1.

The Android code mainly has 3 parts : Activities , Layout and Android manifest.

1. MainActivity.java

   When the application is opened, the first executed code is the MainActivity.java. In this code the basic resources of the codes are described. This activity defines the initial instances of the application.

2. activity-main.xml

   This is the layout code for the MainActivity.java. We can specify the dimensions of the screen in this file. And the ids and behavior of different items are defined in this file. This id's can be later used in the activities.

3. AndroidManifest.xml

   The full details about the applications are given in this file. The following information are provided by the Androidmanifest.xml. Minimum SDK version and the target SDK version used. The theme used in the App. The permissions which are enabled. All the activities in the App are to be included in it.

6.3.1 Android Application

The Android application can be used to detect and classify Apnea based on there severity. The application consists of 3 layouts : The main activity layout, the analysis activity layout and the plot layout.

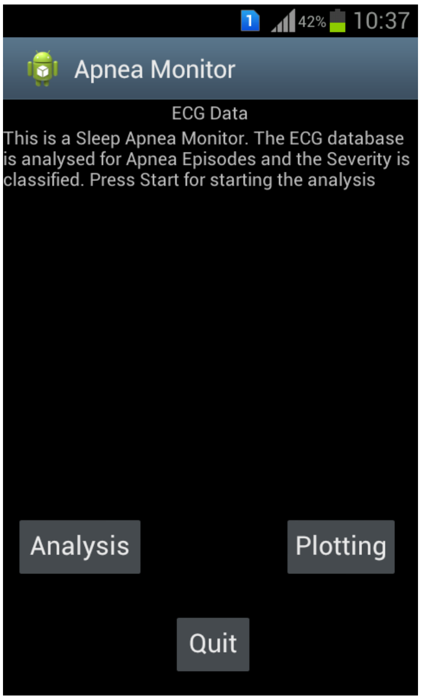

Figure 6.24: *Application Main Layout*

The main layout consist of 3 buttons : Analysis , Plotting and Quit. On clicking one of this button the application does the denoted application.

Analysis

When the Analysis button is pressed, the control goes to the analysis section of the Application. Here, the Analysis layout of the application is loaded.

Basically, the application classifies the data in to 4 different categories: Severe Sleep Apnea, Moderate Sleep Apnea, Mild Sleep Apnea and Normal Sleep Apnea.

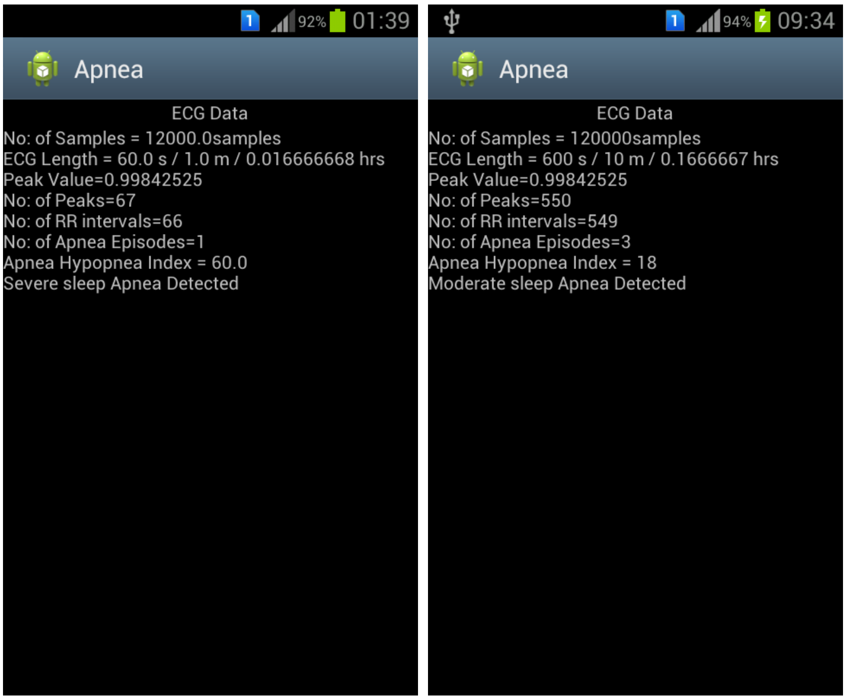

Figure 6.25: *Severe & Moderate Sleep Apnea*

When the no:of Sleep Apnea Episodes in an hour is more than 30, that is the Apnea-Hypoapnea Index is greater than 30, then the ECG data was classified as Severe Sleep Apnea.

When the no:of Sleep Apnea Episodes in an hour lies in between 14 and 30, that is the Apnea-Hypoapnea Index is greater than 14 and less than 30, then the ECG data was classified as Moderate sleep Apnea.

However classified as Severe and Moderate Sleep Apnea, both the cases are considered as extreme cases of sleep apnea and need immediate diagnosis and treatment.

When the no:of Sleep Apnea Episodes in an hour lies in between 4 and 14, that is the Apnea-Hypoapnea Index is greater than 4 and less than 14, then the ECG data was classified as Mild sleep Apnea.

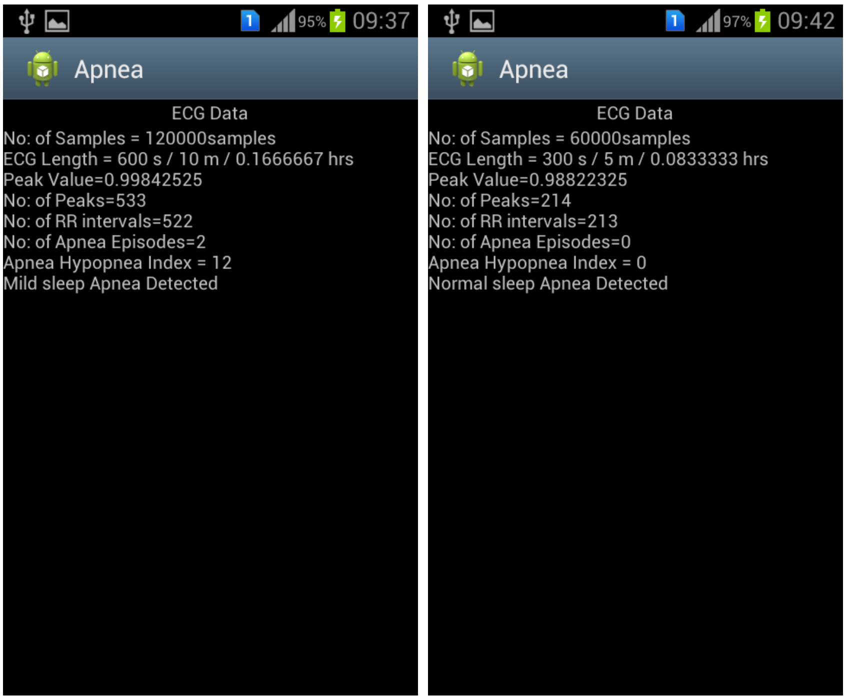

Figure 6.26: *Mild & Normal Sleep Apnea*

The Mild Sleep Apnea cases are considered as less severe than Moderate Sleep Apnea. However treatment is required, it is not as critical as the severe and and Moderate Sleep Apnea's.

When the no:of Sleep Apnea Episodes in an hour is less than 4, that is the Apnea-Hypoapnea Index is less than 4, then the ECG data was classified as Normal Sleep Apnea.

The normal cases of ECG was classified as Normal Sleep Apnea. Small number of Apnea episodes are normal in human beings.Even if the patient shows the symptoms of sleep apnea episodes, there is no need for worry as these may be triggered by fatigue.

Plotting

When the Plotting button is pressed, the control goes to the Plotting section of the Application. Here, the Plot layout of the application is loaded.

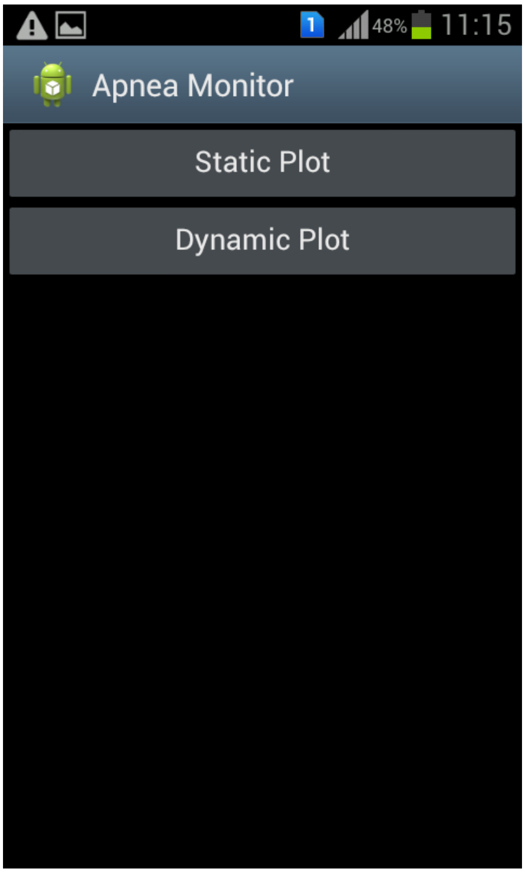

Figure 6.27: *Plot Layout*

Figure 6.39 shows the plot layout of the application. The plot layout consist of three buttons. Pressing each button gives specific plots of the database. Two types of plot are specified : Static plot and the Dynamic plot.

When the button for static plot is pressed, The plot window shows the static plot of the ECG database. When the Dynamic Plot is pressed, the plot window shows the dynamic plot of the database. For dynamically plotting the database a 50 ms timer is used and a new data is plotted every 50 ms.

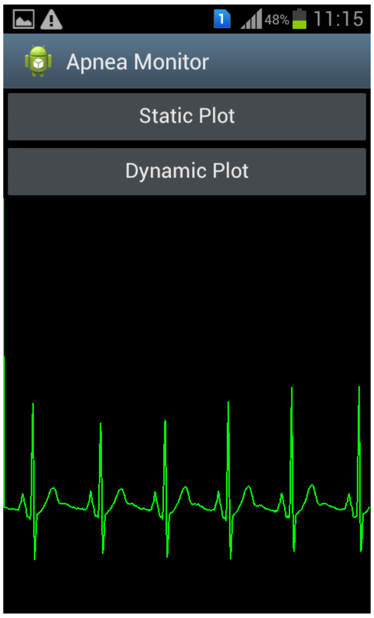

Figure 6.28: Static Plot

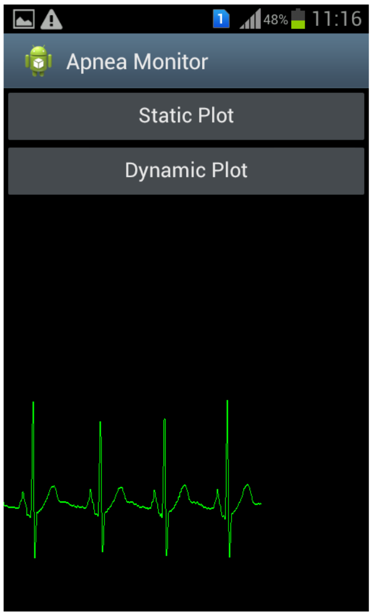

Figure 6.29: Dynamic Plot

6.4 Android Implementation Results

During the previous section of the work, 115 hours of ECG data from the Physionet Sleeep Apnea ECG data base was tested. The following results were obtained.

Table 6.2: ***Android Implementation Results***

Epoch	**RR Diff.**	**NN50**	**Apnea**	**Detected**	**Accuracy**
5 sec	50 ms	4 No’s	4493 No’s	2601 No’s	57.89%
5 sec	55 ms	4 No’s	4493 No’s	2657 No’s	59.14%
5 sec	60 ms	4 No’s	4493 No’s	2834 No’s	63.07%
6 sec	50 ms	4 No’s	4493 No’s	2472 No’s	55.01%
6 sec	55 ms	5 No’s	4493 No’s	2916 No’s	64.9%
6 sec	60 ms	6 No’s	4493 No’s	2983 No’s	66.4%
7 sec	50 ms	4 No’s	4493 No’s	2787 No’s	62.03%
7 sec	55 ms	5 No’s	4493 No’s	3118 No’s	69.4%
7 sec	60 ms	6 No’s	4493 No’s	3304 No’s	73.54%
8 sec	50 ms	5 No’s	4493 No’s	3195 No’s	71.1%
8 sec	55 ms	5 No’s	4493 No’s	3356 No’s	74.7%
8 sec	60 ms	5 No’s	4493 No’s	3375 No’s	75.12%
8 sec	60 ms	6 No’s	4493 No’s	3535 No’s	78.67%
9 sec	60 ms	5 No’s	4493 No’s	3320 No’s	73.9%
9 sec	60 ms	6 No’s	4493 No’s	3421 No’s	76.13%
10 sec	60 ms	6 No’s	4493 No’s	3277 No’s	72.94%

Based on the current calculations it was noted that the maximum accuracy was obtained when the epoch length was 8 sec, The difference in RR interval was 60 ms and the NN50 values (variants 1 and 2) equal to 6. The maximum accuracy obtained was 78.67 %. 5 hours of normal ECG database was tested and 0 Apnea episodes were detected with an accuracy of 100%. However, it was noted that, when multiple Tachycardia or Bradycardia or a combination of these occur, it was detected as a sleep apnea episode.

Chapter 7

CONCLUSION

The Project implements an independent Sleep Apnea detection system from ECG on an Android based platform. Although PSG has been recognized as the golden standard for diagnosing sleep apnea, PSG got many criticisms from some researchers. Therefore a need for simpler technology that has the same reliability with PSG that doesn't require special laboratory is long over due. In this project an attempt is made to implement an easy and less expensive way for detecting Sleep Apnea.

In the current method, Sleep Apnea episodes were detected from the ECG by extracting the RR interval using the Pan-Tompkins algorithm. The Physionet data base is used as the input to the system.The data consist of 70 records, divided into a learning set of 35 records and a test set of 35 records. Out of which, 70 one hour and 5 eight hour apnea database and 5 hours of normal ECG database was tested. The overall accuracy of the system at the current stage, when the epoch length was 8 sec, The difference in RR interval was 60 ms and the NN50 values (variants 1 and 2) equal to 6, was found to be approximately 79%. Therefore, by adding more features for detecting apnea, this method might prove to be a easy and less expensive way for detecting Sleep Apnea.

Chapter 8

FUTURE WORK

More feature should be extracted from the ecg to improve the accuracy of the Apnea Detection. Also by including a Heart Turbulence monitor, the effects and severity of the sleep apnea on our heart may be identified. Also for the accurate classification of different Apnea conditions, a support vector machine (SVM) based or a Neural Network based classification can be used

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