ECG DENOISING USING MULTIPLE THRESHOLDING LEVEL FOR DIFFERENT WAVELET TRANSFORMS

Naveen Kumar Munjal¹ & Dr Shiv Ratan Singh²

¹ Lecturer, Department of ECE, GurrnuNnanakDev Institute of Technology, Rohini,
² Head (I/C), Department of ECE, GurrnuNnanakDev Institute of Technology, Rohini, Delhi

Abstract

Wavelet transform is an effective tool for feature extraction, because this allows analysis of images at various levels of resolution. Considering the Discrete Wavelet Transform (DWT) based wavelet, de-noising has been incorporated using four different thresholding techniques to remove the three major sources of noises from the acquired ECG signals namely, power line interference, baseline wandering, and high frequency noises. SEVEN wavelet functions ("db1", "coif1","rbio1.1" , "dmey" , "bior1.1" ,"haar" and "sym1") and four different thresholding levels (at 0.0056, 0.0156, 0.0256 and 0.0356 levels) were utilised to de-noise the ECG signals. This paper describes the way to process the ECG signals (make them noise-free).

Introduction

Electrocardiogram (ECG) is a nearly periodic signal (quasi periodic) that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyse them. The initial task for efficient analysis is the removal of noise. It actually involves the extraction of the required cardiac components by rejecting the background noise.[15]

The Heart

The heart is a vital organ of the human body. It is a hollow, chambered muscle which is responsible for pumping blood throughout the body and is located in the chest between the lungs. It beats for about 2.5 billion times throughout a person’s life and pumps around 300 litres of blood per hour on an average.

Anatomy of a Heart

The heart consists of four main chambers: the left atrium, the right atrium, the left ventricle and the right ventricle. The atria receive blood while the ventricles discharge blood. The left and the right sides of a heart are divided by a thick wall of muscle known as septum. Three layers constitute the outer wall of the heart. The outer layer is called the epicardium, the middle layer is called the myocardium and the inner layer is called the endocardium.

Pumping

The heart supplies blood to the body by a process known as pumping. In this process, the right atrium receives oxygen-deficient blood from the body through the superior and inferior cava, while the left atrium receives oxygen-rich blood from the lungs through the pulmonary veins. The right atrium transfers the blood to the right ventricle through the tricuspid valve when it is filled with blood. At the same time, the left atrium contracts and the mitral valve opens, then blood is pumped into the left ventricle. The valves are closed after the ventricles have received blood, filled with blood, the ventricles contract with the left ventricle contracting an instant before the right ventricle. When the left ventricle starts to contract, the aortic valve between the left ventricle and the aorta opens and that contraction is what
pumps oxygen-rich blood into the rest of the body through the aorta. At the same time the right ventricle contracts and the pulmonary valve opens to let the blood flow into the lungs through the pulmonary artery. This perpetual motion of the heart is known as pumping.[15]

Electrical Characteristics of Heart

A region of the human heart called the sinoatrial node generates electrical impulses which spread rapidly through the walls of the atria, causing both atria to contract in unison. The electrical impulse arrives at the atrioventricular node (AV) located on the floor of the right atrium. At the AV node the impulse is delayed for about 0.1s before spreading to the walls of the ventricle. The delay ensures that the atria are empty completely before the ventricles contract. Specialized muscle fibers called Purkinje fibers then conduct the signals to the apex of the heart along and throughout the ventricular walls. This entire cycle, a single heartbeat, lasts about 0.8 seconds. The impulses generated during the heart cycle produce electrical currents, which are conducted through body fluids to the skin, where they can be detected by electrodes and recorded as an electrocardiogram.

ECG

Introduction

An electrocardiogram is a test that analyses the electrical activity of the heart. In an ECG test, the electrical impulses are recorded with the help of ECG apparatus and then printed on a paper. This is known as an electrocardiogram, and records any problems with the heart's contractions or any latent heart disease.

Technique

An electrocardiogram is obtained by attaching 10 electrodes to the body, which assist the ECG machine in recording the heart activity. Six of these electrodes are placed on the person’s chest while the rest four are placed on the limbs of the person. The ECG device detects and amplifies the tiny electrical changes on the skin that are caused when the heart muscle depolarizes during each heartbeat. During each heartbeat, a healthy heart will have an orderly progression of a wave of depolarisation that is triggered by the cells in the senatorial node, spreads out through the atrium, and passes through the atroventricular node and then spreads all over the ventricles. The ECG machine records this onto a paper which is then read like a graph. The graph has time on the x-axis and the voltage on the y-axis. Physicians then analyse the graph for diagnosis.

Leads

Lead refers to an imaginary line between two ECG electrodes. The electrical activity of this lead is measured and recorded as part of the ECG. A 12-lead ECG records 12 of these “leads” producing 12 separate graphs on the ECG paper. However you only actually attach 10 physical electrodes to the patient.

Different kinds of leads are –

The Standard Leads (Bipolar)

Leads which have one positive and one negative pole are called bipolar leads. By attaching electrodes to the left arm, which is a positive pole and the right arm as a negative one - designated as Lead I - a potential difference between them is recorded. Another possible position is to attach the right arm as a negative pole and the left leg as a positive one; this is named as Lead II. When we attach the electrode to the left arm as a negative pole and the left leg as a positive one, this makes lead III. Each of these leads measures the voltage between two points on the body.

Figure1.1 The Standard Leads (Bipolar)
The Augmented Leads (Unipolar)

Three additional limb leads can be obtained by recording a potential difference between an imaginary central neutral point based on two electrodes connected together to create an “average” electrode and finally connected through the ECG machine to the remaining electrodes, as shown in Figure 1.5. These leads are VR, aVL, and aVF.

The Chest Leads (Unipolar)

In addition to the three standard limb leads and the three augmented limb leads, there are six leads labeled as "V" leads, noted as V1 to V6 as shown in Figure 1-6. This configuration places six positive electrodes at specific positions on the rib cage.

The ECG Waveform

To understand the genesis of the ECG waveform, it is useful to consider first the basic anatomy and function of the heart. The heart is a four-chambered pump which provides the driving force for the circulation of the blood around the body. A wall divides the heart cavity to form a double-pump configuration. Each side of the heart is then further divided into an upper chamber known as the atrium, and a lower chamber known as the ventricle. The atria and the ventricles in the heart are composed of muscle cells (or “myocytes”).

The rhythmic contractions of the heart stem from the flow of ions through channels in the membranes of the heart’s muscle cells. The cell membrane is the dividing medium between the extracellular and the intracellular fluids, each of which has a different ionic concentration. When a cell is stimulated electrically, the permeability of the membrane to ionic transfer are modified. The resulting flow of ions through the cell membrane gives rise to an electrical signal known as an action potential. This in turn results in a mechanical contraction of the cell.

The propagation of action potentials through the atria and the ventricles during each heartbeat results in a set of distinct features in the characteristic ECG waveform. These features represent either depolarisation (electrical discharging) or repolarisation (electrical recharging) of the heart muscle cells in the atria and the ventricles.

ECG Features

Main Features

The standard features of the ECG waveform are:

- The P wave
- The QRS complex
- The T wave

Additionally a small U wave (following the T wave) is occasionally present. The origin of the U wave is uncertain; however it is believed that small U waves and large U waves have different physiological origins.
ECG Interval Analysis

The timing between the onset and offset of particular features of an ECG waveform is referred to as an interval. Measurements of the ECG intervals are of great importance since they provide an indirect measure of the state of the heart and can be indicative of the presence of certain cardiological conditions.

Figure overleaf shows a typical ECG waveform and the three standard ECG intervals. These are known as the QT interval, the PR interval and the QRS duration. We now consider each of these in turn.

QT interval:

Perhaps the most important timing interval in the ECG waveform is the QT interval. The QT interval is defined as the time from the start of the QRS complex to the end of the T wave, i.e. Toff – Q. It corresponds to the total duration of electrical activity (both depolarisation and repolarisation) within the ventricles in a given heartbeat.

It is important to recognise that the QT interval varies according to the particular ECG lead selected for analysis. Thus, the QT intervals measured from the same heartbeat on a number of different leads will typically have a range of different values.

Figure 1.4 An ECG waveform showing together with the standard ECG intervals.

Long QT syndrome:

Long QT syndrome (LQTS) refers to the condition whereby the QTc interval is prolonged with respect to its normal range of values. Table 1.1 shows the accepted ranges of normality for the corrected QT interval.

Long QT syndrome is an extremely serious condition that renders sufferers vulnerable to a very fast, abnormal heart rhythm (an “arrhythmia”) known as torsade de pointes.

Although this heart rhythm is itself not fatal, it can in some circumstances degenerate into ventricular fibrillation, a rapidly fatal arrhythmia. When this occurs the heart is unable to beat effectively and the blood flow to the brain falls dramatically.

result is a sudden loss of consciousness quickly followed by cardiac death.

Long QT syndrome can be either inherited (the genetic form) or acquired. The inherited form is believed to be present in as many as 1 in 5000 people in the USA alone and may cause as many as 3000 deaths (mostly in children and young adults) each year. The acquired form of LQTS generally results from the administration of certain drugs which lengthen the duration of ventricular repolarisation in each heartbeat. This issue, and its importance in the context of clinical drug trials.

PR interval:

The PR interval is defined as the time from the start of the P wave to the start of the QRS complex, i.e. Q – Pon. It corresponds to the time from the onset of atrial depolarisation to the onset of ventricular depolarisation.

The PR interval has precise time limits in health. In particular, it should be in the region of 0.12 to 0.2 seconds long. Drug-induced prolongation of the PR interval indicates that the drug slows atrioventricular conduction, which can in turn lead to “heart block”.

QRS duration:

The QRS duration (QRSd), i.e. J – Q, corresponds to the duration of ventricular depolarisation in each heartbeat. In health its value is normally no longer than 0.12 seconds. Drug-induced prolongation of the QRS duration indicates that the drug delays the time taken for conduction through the ventricles. This effect has the potential to cause arrhythmias.

Literature survey:

With this aim, I did an extensive literature [2] [3] survey which involved exhaustive research for available research papers, databases and related information. Th ese survey was performed with core depthandsand and Populardatabases which contain information about the ECG signals (both normal and abnormal) were carefully examined and valuable information was gathered.

Various reputed journals were regularly reviewed and any relevant information from the field of Bio-
medicalEngineeringwastraduced. After an exhaustive literature survey, we gathered enough information from various ECG signals. After reviewing various research papers regarding ECG signal processing and analysis, we finally decided to obtain data from MIT-BIH arrhythmia database as it was the most reputed and reliable database available. It has about 500 samples of ECG signals and hence, data screening was very important.

Electrocardiogram traces used for identification are obtained using surface electromyography (EMG), where electrodes are placed on the skin in the vicinity of the heart. Potential differences of 1 to 3 mV generated at the body surface by the current sources in the heart are picked up by the electrodes and are amplified in order to improve the signal to noise ratio (SNR). The ECG waveform is observed on an oscilloscope or is digitized for further processing by a computer. The digitization process should use a sampling rate of at least 1 kHz to ensure that the ECG trace is of a high enough resolution as required for biometric purposes.

ECG measurements may be corrupted by many sorts of noise. The ones of primary interest are:

1. Power line interference,
2. Electrode contact noise,
3. Motion artefacts,
4. EMG noise, and
5. Instrumentation noise

**ECG Denoising using several methods:**

**Empirical Mode Decomposition:**

The basis functions used to decompose a signal are not predefined but adaptively derived from the signal itself; especially applicable for nonlinear and non-stationary signals, including ECG.[5]

**Intrinsic Mode Function:**

By definition, an IMF should satisfy two conditions:

The total number of local extreme and that of zero crossings should be equal to each other or different by at most one, and the mean of the upper and lower envelopes respectively defined by local maxima and local minima should be zero.

De-noising in ECG Signal Based on EMD and Adaptive Filter

**Advantages:**

It is relatively easy to be implemented in software and hardware due to its computational simplicity and efficient use of memory.

**Drawback:**

Also the tracking of the changes in the input of the filter depends on the step size. LMS.[13] has the disadvantage of getting stuck to a local minimum point.

**Independent Component Analysis:**

Separate mutually independent components from mixed signal, which is linear combination of a set of mutually independent source signals. Applied to remove the interference of ECG signal preserves the original details information as soon as possible and filter the interference signal successfully.[14]

Denoising in ECG Signal Based on EMD and Adaptive Filter

This method consists of two main functional blocks:

The reconstructed reference signal based on EMD.[5]
The adaptive unit based on LMS algorithm.[13]

**Advantages:**

It is fast and computationally simpler.

Its response is better in real-time applications.

**Drawbacks:**

Only capable of removing noise caused due to power line interference. Wavelet Transform in the Processing for ECG Signals.

Wavelet Transform is used to scale decompose ECG signals with noises into different frequency bands, then, we remove some "details" (a variety of noises), finally, we adopt the wavelet to reconstruct and restore useful signals to get ECG signals without noises.

**Methodology:**

The aim of our project was to process the ECG signals[12] (make them noise-free). We have used the SEVEN wavelet functions for level 4 Standard wavelet families, including Daubechies wavelet filters, complex Morlet and Gaussian, real reverse biorthogonal, and discrete Meyer.

Using the toolbox we generated the code for the require d wavelet transforms and used the generated code for denoising the signals. Also, percentage denoising was calculated, keeping into account the noise in the original signal and the noise in the denoised signal. Thus the need is there for computer-based methods for ECG signal Analysis.[10]

ECG Signal processing involves the following steps:

![Fig.1.1 Basic Block Diagram](image)

**Wavelet Transform:**

A wavelet is a “small wave” of varying frequency and limited duration. Using narrow windows for analyzing high frequencies and wide windows for analyzing low frequencies works quite well for signals having high frequency components for short durations and low frequency components for long durations.[16]

Wavelets provide simultaneous localization in time and scale (i.e., frequency). The location of the wavelet allows to explicitly represent the location of events in time. The shape of the wavelet allows to represent different detail or resolution.
Continuous wavelet transform of the signal $f(t)$

The mother wavelet. All kernels are obtained by translating (shifting) and/or scaling the mother wavelet.

Scale $= 1/$frequency

$$CWT_f^\psi = \frac{1}{\sqrt{s}} \int f(t) \psi^* \left( \frac{t - \tau}{s} \right) dt$$

(Forward CWT)
We have considered the Discrete Wavelet Transform (DWT) based wavelet de-noising, incorporated using four different thresholding techniques to remove three major sources of noises from the acquired ECG signals namely power line interference, baseline wandering, and high frequency noises. SEVEN wavelet functions ("db1", "coif1", "rbio1.1", "dmey", "bior1.1", "haar" and "sym1") and four different thresholding levels (0.0056, 0.0156, 0.0256 and 0.0356) are used to de-noise the noise in ECG signals.

Wavelet Transform in the Processing for ECG Signals:
First of all, Wavelet Transform[1] is used to scale decompose ECG signals with noises into different frequency band signals. Then, some "details" (a variety of noises) are removed & finally, we adopt the wavelet to reconstruct and restore useful signals to get ECG signals without noises.[1]

If the signal \( f(t) \) is reconstructed by the basic function of Wavelet Transform, its definition of inverse-transform is such as the formula

\[
f(t) = \frac{1}{C_\psi} \int_{\infty}^{\infty} \int_{\infty}^{\infty} W_f(a,b) \psi_{a,b}(t) \frac{1}{a^2} \, da \, db
\]

\[
C_\psi = \int_{-\infty}^{\infty} \left| \psi(w) \right| dw
\]

\[ \cdots \cdots (4.4) \]

Where \( w \) is a continuous quantity and \( (w) \psi \) is Fourier Transform of \( \psi(t) \).

Wavelet Transform which decomposes the signal to the superimposition of a series of wavelet produced by the basic wavelet after companding and moving in parallels, is a localized time-frequency analysis method, that is, it has the lower temporal resolution and the higher frequency resolution in the low frequency part, and has the lower frequency resolution and the higher temporal resolution in the high frequency part. It has the automatic adaptive characteristics for signals, which is particularly suited to deal with ECG signals.

Wavelet threshold value eliminating noises:
In the wavelet domain, the signal[5] energy relatively concentrates in a few locations, but noises distribute more widely. According to the transient nature, signals often represent some big coefficients, and some small coefficients are generated by the mutation of noises and the signal energy, so the wavelet threshold value eliminating noises mainly uses the different performance characteristics of singularity of effective signals and noises in Wavelet Transform to eliminate noises and retain effective signals, and it has more obvious advantages than traditional methods. The same signal when processed with different wavelet functions gets different results, so the selection of the wavelet function is very important. Based on the characteristics of the ECG signal, most appropriate Wavelet functions that can be applied are: Coiflets wavelet, Daubechies wavelet and Symlets wavelet, "rbio1.1", "dmey", "bior1.1", & "haar". The explained Wavelet Denoising Algorithm is given below.

Continuous Wavelet Transform (CWT):
Wavelet transform can be defined as

\[
[W_\psi f] (a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \psi \left( \frac{x - b}{a} \right) f(x) \, dx
\]

The wavelet coefficients \( c_{jk} \) are the given by
\[ c_{jk} = [W \psi f] \left( 2^{-j}, k:2^{-j} \right) \]

Here, \( a = 2^{-j} \) is called the binary dilation or dyadic dilation, and \( b = k:2^{-j} \) is the binary dyadic position.

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.

**Thresholding:**

Wavelet thresholding is the signal estimation technique that exploits the capabilities of signal denoising. Thresholding method is categorized into two types – hard thresholding and soft thresholding. [4] The hard thresholding function tends to have big variance and is unstable. Its change is minor. However, soft thresholding function is much more stable than hard thresholding and tends to have a bigger bias due to thresholding wavelet coefficients. In general, it has been proved that soft thresholding method gives the best result with other methods of denoising the ECG signal.

Signal denoising using the DWT consists of the three successive procedures namely - signal decomposition, thresholding of the DWT coefficients, and signal reconstruction. Firstly, we carry out the wavelet analysis of noise signal up to a chosen level \( N \). Secondly, we perform thresholding of the detail coefficients from level 1 to \( N \). Lastly, we synthesize the signal using the altered detail coefficients from level 1 to \( N \) and approximate coefficients of level \( N \). However, it is generally impossible to remove all the noise without corrupting the signal. [6]

**Wavelet Denoising Algorithm:**

Initially, decompose the input signal [7] using DWT ("db1", "coif1", "rbio1.1", "dmey", "bior1.1", "haar" and "sym1"): Choose a wavelet and determine the decomposition level of a wavelet transform. Then, implement \( N \) levels of wavelet decomposition of signal S.

Select the thresholding level and thresholding rule for quantization of wavelet coefficients. Apply the thresholding oneach level of wavelet decomposition.

Finally, reconstruct the denoised signals without affecting any features of signal interest. Performing the Inverse Discrete Wavelet Transform (IDWT) of various wavelet coefficients for each decomposition level does the reconstruction.

From the above three steps, the most critical is to select the proper threshold because it directly reflects the quality of the denoising. [11]

**Wavelet Thresholding on ECG Signals:**

The ECG signals are severely affected by using different sources of noises such as power line frequency, base line wandering & high frequency noises. However, it is impractical to remove the noises visually
Using the coiflet wavelet at 0.0056,
thresholds for different patients are plotted.
The results of different wavelets at different
thresholds are compared which gives a
conclusive remark about the accuracy of
noise removed. The results for individual
wavelets are as follows:

**Fig. 1:** Using the coiflet wavelet at 0.0056,
0.0156, 0.0256 and 0.0356 threshold levels
with different patients, observations were
made and the following graph was plotted.

It is observed that noise is more successfully
detected for the thresholds 0.0256 and
0.0356. However, the later can be
considered a better result than former since
only two patients (209m and 809m) of
eleven show better noise value for threshold
0.0256 (25.8218 to 24.5461 and 16.118 to
13.9261 respectively). For a better intuition
on the coiflet wavelet results among
different patients a table is given below
(TABLE I). The maximum value of each
patient is highlighted next to its threshold.

**Fig. 2:** Using the dblet wavelet at 0.0056,
0.0156, 0.0256 and 0.0356 threshold levels
with different patients, observations were
made and the following graph was plotted.

It is observed that noise is more successfully
detected for the threshold 0.0356. Patients
100m, 115m, 209m, 234m, 300m, 313m,
800m, 16272m, 16733m, and 16786m gave
the results 38.2698, 24.0276, 28.048,
30.9285, 23.1219, 25.8542, 23.4153, 25.8542,
23.4153, 10.0498 and 12.2562 respectively. Patient 809m gave the
value 16.3443 to a 17.5988 for the threshold
0.0256. For a better intuition on the dblet
wavelet results among different patients a
table is given below (TABLE I). The
maximum value of each patient is
highlighted next to its threshold.

**Results:**

The results of different wavelets at different
thresholds for different patients are plotted
in amount of noise versus patient graphs. We
observe the noise detected by different
wavelets at different thresholds. Then all
the wavelets with their best-observed
thresholds are compared which gives a
conclusive remark about the accuracy of
noise removed. The results for individual
wavelets are as follows:

**Fig. 1:** Using the coiflet wavelet at 0.0056,
0.0156, 0.0256 and 0.0356 threshold levels
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made and the following graph was plotted.

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wavelet results among different patients a
table is given below (TABLE I). The
maximum value of each patient is
highlighted next to its threshold.
Fig. 3: Using the sym wavelet at 0.0056, 0.0156, 0.0256 and 0.0356 threshold levels with different patients, observations were made and the following graph was plotted.

In sym wavelet best noise is observed for the threshold 0.0256. Patient 16272m, 16773m and 16786m had almost the same result for the threshold 0.0256 and 0.0356 (20.8637 to 20.4531, 8.6301 to 8.0868 and 10.5417 to 10.1504 respectively). For a better intuition on the sym wavelet results among different patients a table is given below (TABLE I). The maximum value of each patient is highlighted next to its threshold.

Fig. 4: Using the rbio wavelet at 0.0056, 0.0156, 0.0256 and 0.0356 threshold levels with different patients, observations were made and the following graph was plotted.

This graph makes it clear that the best threshold for the rbio wavelet is 0.0356 as maximum noise is observed for each patient. For a better intuition on the rbio wavelet results among different patients a table is given below (TABLE I). The maximum value of each patient is highlighted next to its threshold.

Fig. 5: Using the dmey wavelet at 0.0056, 0.0156, 0.0256 and 0.0356 threshold levels with different patients, observations were made and the following graph was plotted.

The best-observed threshold is 0.0256 for almost all patients throughout. For patient 100m noise is maximum at threshold 0.0356. For patient 809m, the threshold 0.0356 (13.8973), almost reaches the noise from threshold 0.0256 (13.8756). For a better intuition on the dmey wavelet results among different patients a table is given below (TABLE I). The maximum value of each patient is highlighted next to its threshold.

Fig. 6: Using the bior wavelet at 0.0056, 0.0156, 0.0256 and 0.0356 threshold levels with different patients, observations were made and the following graph was plotted.

For the bior wavelet the observed values make it evident that noise is best recorded at threshold 0.0356. For a better intuition on the bior wavelet results among different patients a table is given below (TABLE I). The maximum value of each patient is highlighted next to its threshold.

Fig. 7: Using the haar wavelet at 0.0056, 0.0156, 0.0256 and 0.0356 threshold levels with different patients, observations were made and the following graph was plotted.

The results for haar wavelets are exactly like the results of the bior wavelets under these thresholds.

Fig. 8: The plot shows the best threshold value results for each of the wavelets. It is observed that as the threshold increases, so does the noise detected by each wavelet.

The wavelets haar, db, bior and rbio share the same plot of threshold 0.0356 for best noise detection. The plot for dmey and sym wavelets almost coincide for the threshold 0.0256 with the exception of patient 809m. For patient 809m the value of dmey wavelet for threshold 0.0256 (13.8973) is almost equal to that of threshold 0.0356 (13.8756). The plot of coiflet wavelet is taken at the threshold 0.0356, values of which almost coincide with those of sym and dmey wavelets for patient 16272 (20.6182, 20.8637 and 20.8637 respectively).
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<th>THRESHOLD LEVEL</th>
<th>WAVELETS</th>
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REFERANCES

2. Smita Kasar, Dr. Madhuri Joshi. "ECG Signal Processing: A survey"