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ECG DENOISING USING MULTIPLE THRESHOLDING LEVEL FOR DIFFERENT WAVELET TRANSFORMS

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Abstract

Wavelet transform is an effective tool for feature extraction, because this allows analysis of images at various levels of resolution. Consideringthe Discrete Wavelet Transform (DWT) based wavelet, de-noising has been incorporated using four different thresholding techniques to removethe 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 theway toprocesstheECGsignals(makethemnoise-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 analysethem. 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 theventricles 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 atrio ventricular 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 artria 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 theventricular 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 atrioventricular 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.

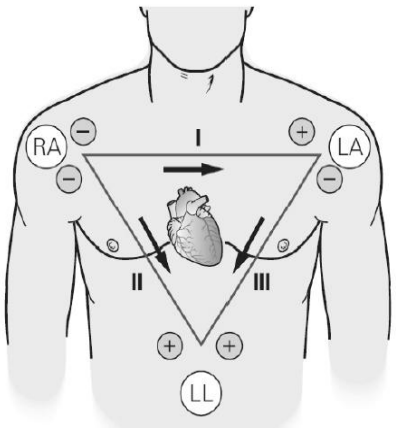


Figure1.1The Standard Leads(Bipolar)

The Augmented Leads (Unipolar)

Threeadditionallimbleadscanbeobtainedbyrecordi ngapotentialdifferencebetween animaginarycentralneutralpointbasedontwoelectr odesconnectedtogethertocreate an“average”electrodeandfinallyconnectedthrough theECGmachinetotheremaining electrodes,as shown inFigure1-5.TheseLeadsareaVR, aVLand aVF

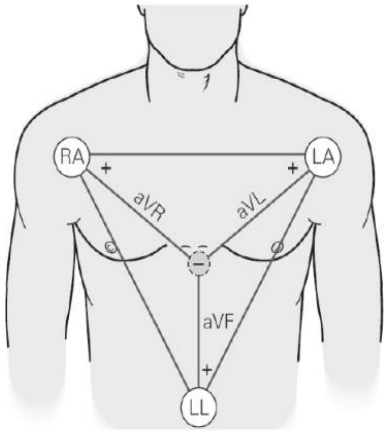


Figure 1.2 The Augmented Leads (Unipolar)

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.

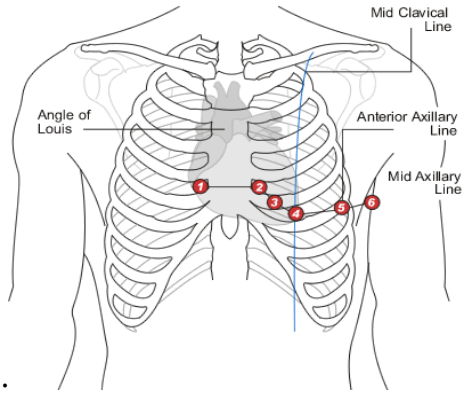


Figure 1.3 The Chest Leads (Unipolar)

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 heart- beat 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) withinthe 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)

Figure1.4 AnECG waveformshowingtogether withthestandardECGintervals.

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. The 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 sart 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:

Withthisaim,Ididanextensiveliterature[2] [3]surveywhichinvolvedan exhaustive researchfor available researchpapers,databasesandrelatedinformation.Th esurveywasperformedwith coredepthand Populardatabases which contain information about the ECG signals (both normal and abnormal) were carefully examined and valuable information was gathered. Various reputedjournalswereregularlyreviewedandanyrelev antinformationfromthefieldof Bio-

medicalEngineeringwasretrieved. Afteranexhaustiveliteraturesurvey,wegatheredsuffi cientdataofvariousECGsignals. After reviewingvariousresearch papersregardingECGsignal processingandanalysis,wefinallydecidedto obtain data fromMIT-BIH arrhythmiadatabaseasitwas themostreputed andreliabledatabaseavailable.Ithasabout 500 samplesof ECG signalsand hence,datascreeningwasveryimportant.

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:

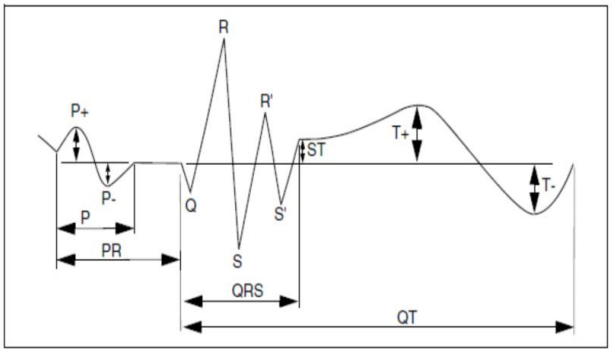
Thebasis functions used to decompose a signal are not predefined but adaptively derived from the signal itselfespecially applicable for nonlinear and non-stationary signals, including ECG.[5]

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.

The first IMF is a good representation of the power line interferences.Approximate power lineinterference can be acquired by the selective reconstruction of IMFs which can be regarded as the inference signal of adaptive filter.



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 struck 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 signalpreserve 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 onLMS algorithm.[13]

Advantages:

It is fast and computationally simpler.

Its response is batter 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 band signals, 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:

TheaimofourprojectwastoprocesstheECGsignals[12](makethemnoise-free).We haveusedthe SEVEN wavelet functions for level 4 Standard wavelet families,including Daubechieswavelet filters, complex Morlet and Gaussian,realreversebiorthogonal,anddiscreteMeyer.
Usingthetoolboxwegeneratedthecodeforthe requiredwavelettransformsandusedthe generatedcode fordenoisingthesignals.Alsopercentagedenoisingwascalculated,keeping intoaccount the noiseintheoriginalsignaland thenoiseinthedenoisedsignal. Thus the need is there for computer based methods for ECG signal Analysis.[10]

ECG Signal processing involves the following steps:

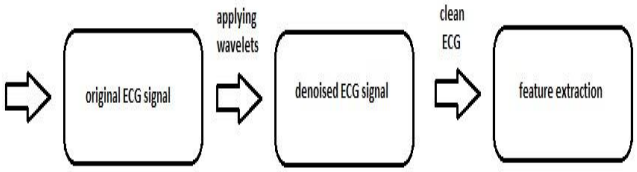


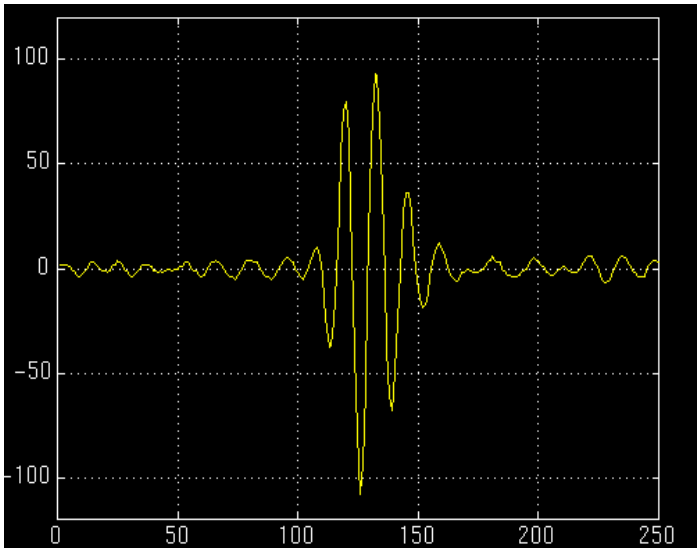
Fig.1.1 Basic Block Diagram

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 waveletallowsto explicitly represent the location of events in time. The shape of the wavelet allowstorepresentdifferent detail or resolution.



Wavelet Function

Translation parameter, measure of time

Scale parameter, measure of frequency

Normalization constant

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

(forward CWT)

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

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

$$f(t) = \frac{1}{C_\psi} \iint_{\infty} \frac{W_f(a,b)\psi_{a,b}(t)}{a^2} dadb$$

$$C_\psi = \int_{+\infty}^{-\infty} \frac{\left|\overset{\Lambda}{\psi}(w)\right|}{|w|} dw$$

…… (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):

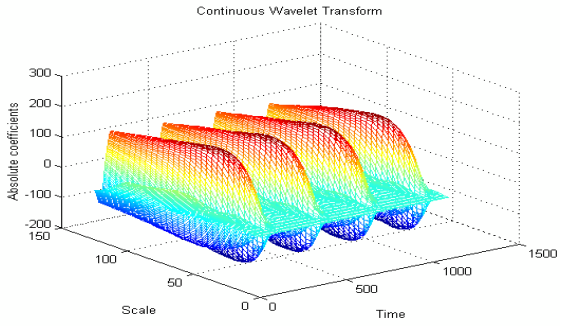
Wavelet transform can be definedas

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

Thewavelet coefficients c_{jk} are the givenby

$$c_{jk} = [W_\psi f]\left(2^{-j}, k2^{-j}\right)$$

Here, $a = 2^{-j}$ is called thebinary dilation ordyadic dilation, and $b = k2^{-j}$ is thebinary ordyadicposition.



Acontinuouswavelet transform(CWT) is used to divide acontinuoustimefunction into wavelets.UnlikeFouriertransform,thecontinuouswavelettransformpossessesthe abilitytoconstruct a time-frequencyrepresentationofasignalthatoffersverygoodtime and frequency localization.

Thresholding:

Waveletthresholdingisthesignalestimationtechniquethatexploits thecapabilitiesof signalde-noising. Thresholding method is categorized into two types- hard thresholdingandsoft thresholding.[4] Thehard thresholdfunctiontendstohavebiggervariance anditisunstable(sensitiveevensmall changesinthesignal).However,softthresholdingfunctionis much more stablethanhard thresholdingandtendstohaveabiggerbiasduetotheshrinkageoflarger wavelet coefficients.Ingeneral,it has been provedthatsoftthresholdingmethodgivestheb estresultswithothermethodsonde-noisingtheECG signal.

SignalDenoisingusingtheDWTconsistsofthe threesuccessiveproceduresnamely-signal decomposition,thresholdingoftheDWTcoefficients,andsignalreconstruction.Firstly,we carryoutthewaveletanalysisofanoisysignaluptoachosenlevelN.Secondly,weperform thresholdingofthedetailcoefficientsfromlevel1 toN.Lastly,wesynthesizethesignal usingthealtereddetailcoefficients fromlevel1toNandapproximationcoefficientsoflevel N.However,itisgenerallyimpossibletoremoveallthenoisewithoutcorruptingthesignal.[6]

Wavelet Denoising Algorithm:

Initially,decomposetheinputsignal[7] usingDWT("db1", "coif1", "rbio1.1", "dmey", "bior1.1", "haar" and "sym1"):Chooseawaveletanddetermine thedecompositionlevelofawavelettransform N,thenimplementN layers waveletdecompositionofsignalS.

Selectthethresholdinglevelsandthresholding ruleforquantizationofwavelet coefficients.Applythethresholdingoneachlevelofwaveletdecomposition.

Finally,reconstruct thedenoised signals withoutaffectinganyfeaturesof signalinterest. Performing the Inverse Discrete Wavelet Transform (IDWT) of various wavelet coefficients for each decomposition level does the reconstruction.

Fromtheabovethreesteps,themostcriticalisto selecttheproperthresholdbecause it directly reflects the quality of thede-noising.[11]

WaveletThresholdingonECGsignals:

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

ondefinitedurationoftheacquiredECGsignal anditconsumes more time. Hence,robustsignal processingtechniquesareinevitable toremovesucheffects ofnoisesfromtheECGsignals.Inourproject,w eemployeddifferenttypesof wavelet thresholdingmethodstoremovenoisesfromth eECGsignal.Previousresearchershave used:"db1","coif1"and"sym1"waveletfuncti onforgeneticalgorithmbaseddenoisingin ECG signal .We usedSEVEN wavelet functions[9] ("db1", "coif1", "rbio1.1", "dmey", "bior1.1", "haar" and "sym1") for our de-noising. The soft thresholding method investigated with four differentthresholding levelstoanalysethedenoisingperformanceof ECGsignals.Basedonthe literature,allthenoisesarehavingcertainfrequ encycharacteristicsandrangesare:power line noise(50 Hzor 60 Hz),baseline wander (>1Hz), and high frequency noises (>100). Therefore,theeffectofnoisesinthefrequencys pectrumofacquiredECGliesinbetween (0-500 Hz).Afterhavingcollectedthedataforanalysis andprocessing,aproperplatformtoperform theprocessing was tobechosen.Aftercontemplatingoverallthеop tions,MATLABwas chosenasthemostappropriatesoftware forthisjob. AftergeneratingtheplotoftheinputsignalinM ATLAB,thenextstepistode-noisethe signalandmakeitcompletely noise free. Aftertheliteraturesurvey, we decidedonapplying thewavelettransformasitwas

foundouttobethemostefficientmethodforde-noisingof ECGsignals.[8]

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 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.

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 dmy 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).

TABLE I:
RESULTS OF ALL WAVELETS AT DIFFERENT THRESHOLDS

PATIENT	THRESHOLD LEVEL	WAVELETS						
		coif	db	sym	rbio	dmey	bior	haar
100m	0.0056	16.684	18.7284	16.7653	18.7284	15.9389	18.7284	18.7284
	0.0156	30.0826	32.9962	30.3586	32.9962	27.9529	32.9962	32.9962
	0.0256	32.9098	36.4707	36.4707	36.4707	30.6877	36.4707	36.4707
	0.0356	34.0826	38.2698	34.3952	38.2698	31.3943	38.2698	38.2698
115m	0.0056	10.4707	11.7429	10.5437	11.7429	9.9309	11.7429	11.7429
	0.0156	17.7298	19.9633	17.7781	19.9633	15.3525	19.9633	19.9633
	0.0256	20.1547	22.6643	22.6643	22.6643	22.6643	22.6643	22.6643
	0.0356	21.1052	24.0276	21.0497	24.0276	18.4903	24.0276	24.0276
209m	0.0056	9.4721	11.2775	9.5504	11.2775	9.3612	11.2775	11.2775
	0.0156	19.0654	21.6721	19.1692	21.6721	17.8173	21.6721	21.6721
	0.0256	25.8218	25.8218	25.8218	25.8218	25.8218	25.8218	25.8218
	0.0356	24.5461	28.048	24.8628	28.048	23.3459	28.048	28.048
234m	0.0056	9.4218	11.1711	9.4745	11.1711	9.1526	11.1711	11.1711
	0.0156	16.3554	19.4263	16.4279	19.4263	14.3381	19.4263	19.4263
	0.0256	19.3162	22.8718	22.8718	22.8718	22.8718	22.8718	22.8718
	0.0356	20.9283	24.9077	21.1061	24.9077	18.4516	24.9077	24.9077
300m	0.0056	8.7707	11.5122	8.84	11.5122	7.7412	11.5122	11.5122
	0.0156	18.9817	22.581	19.1176	22.581	16.3427	22.581	22.581
	0.0256	23.9371	27.9136	27.9136	27.9136	27.9136	27.9136	27.9136
	0.0356	26.5642	30.9285	26.7055	30.9285	23.539	30.9285	30.9285
313m	0.0056	6.6363	8.4967	6.6185	8.4967	5.796	8.4967	8.4967
	0.0156	13.9083	16.5104	13.9476	16.5104	11.9333	16.5104	16.5104
	0.0256	17.6962	20.6288	20.6288	20.6288	20.6288	20.6288	20.6288
	0.0356	19.9107	23.1219	20.1806	23.1219	17.5319	23.1219	23.1219
800m	0.0056	9.5216	10.588	9.4851	10.588	8.9482	10.588	10.588
	0.0156	18.7047	20.4693	18.6217	20.4693	17.0766	20.4693	20.4693
	0.0256	21.4084	23.9613	23.9613	23.9613	23.9613	23.9613	23.9613
	0.0356	22.729	25.8542	22.653	25.8542	20.5075	25.8542	25.8542
809m	0.0056	4.1864	4.5403	4.1447	4.5403	3.9245	4.5403	4.5403
	0.0156	9.2819	10.4002	9.4996	10.4002	8.9693	10.4002	10.4002
	0.0256	16.1882	17.5988	17.5988	13.8973	13.8973	13.8973	13.8973
	0.0356	13.9261	16.3443	14.3738	16.3443	13.8756	16.3443	16.3443
16272m	0.0056	7.0013	7.7519	6.997	7.7519	6.2353	7.7519	7.7519
	0.0156	14.8404	16.5858	14.7939	16.5858	12.6783	16.5858	16.5858
	0.0256	18.4886	20.8637	20.8637	20.8637	20.8637	20.8637	20.8637
	0.0356	20.6182	23.4153	20.4531	23.4153	16.7644	23.4153	23.4153
16773m	0.0056	2.5064	2.931	2.4834	2.931	2.4404	2.931	2.931
	0.0156	5.4886	6.6111	5.5362	6.6111	5.3301	6.6111	6.6111
	0.0256	6.936	8.6301	8.6301	8.6301	8.6301	8.6301	8.6301
	0.0356	7.9407	10.0498	8.0868	10.0498	7.3541	10.0498	10.0498
16786m	0.0056	2.9185	3.5242	2.9321	3.5242	2.3336	3.5242	3.5242
	0.0156	6.7213	7.9684	6.817	7.9684	5.0362	7.9684	7.9684
	0.0256	8.722	10.5417	10.5417	10.5417	10.5417	10.5417	10.5417
	0.0356	9.9835	12.2562	10.1504	12.2562	6.6382	12.2562	12.2562

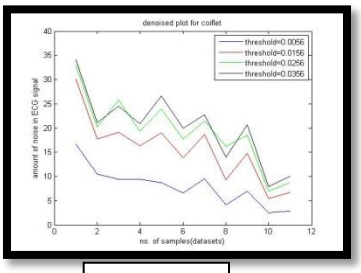


Figure 1

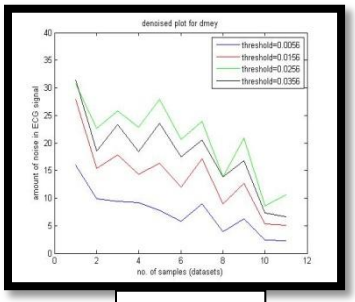


Figure 2

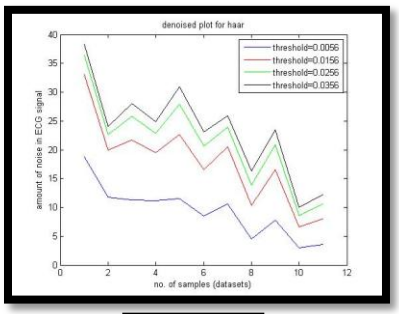


Figure 3

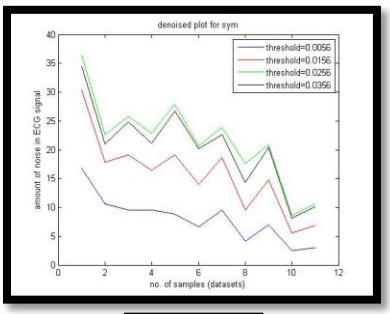


Figure 4

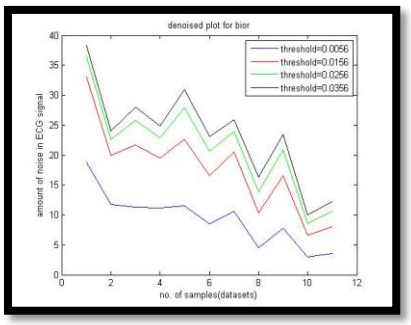


Figure 5

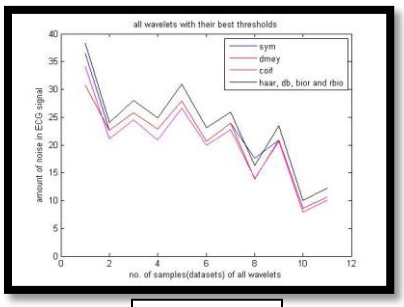


Figure 6

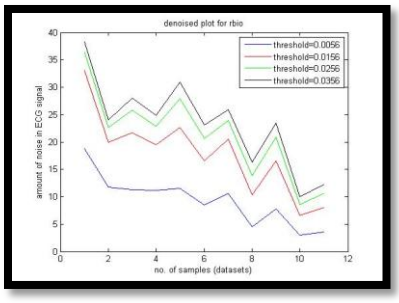


Figure 7

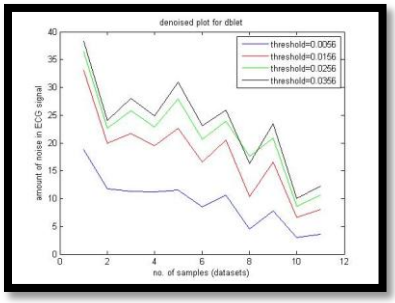


Figure 8

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