Denoising of ECG Signal using Soft Thresholding and Empirical Mode Decomposition

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Abstract – Electrocardiogram (ECG) is used to record the electrical activity of the heart. Electrocardiogram (ECG), a noninvasive technique which is used generally as a primary diagnostic tool for cardiovascular diseases. A cleaned ECG signal provides necessary information about the electrophysiology of the heart diseases and ischemic changes that may occur. The electrocardiographic signals are often contaminated by noise from diverse sources. Different noises of high frequencies and low frequencies are contaminated with ECG signal that may lead wrong interpretations. The noises that commonly disturb the basic electrocardiogram are power line interference, electrode contact noise, motion artifacts, electromyography (EMG) noise, and instrumentation noise. These noises can be classified according to their frequency content.
It becomes very important to minimise these disturbances in ECG signal so that accuracy and the reliability can be improve. In this paper, denoising of the ECG signal is the major objective and technique used for this purpose is based on the Empirical Mode Decomposition (EMD) followed by wavelet based soft thresholding (Rigrsure). The experiments are carried out on MIT-BIH (Massachusetts Institute of Technology Beth Israel Hospital) database.

Keywords – *ECG, MIT-BIH, EMD, EMG, IMF.*

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I. INTRODUCTION

The heart signals are taken from ECG, which is known as Electrocardiography. In the last decade, the research has been centered on the transforming of biomedical signals. Every day clinical practice creates any measure of biomedical signals amid checking of patients and for indicative purposes. Electrocardiogram (ECG) is used to record the electrical activity of the heart. It is a graphical demonstration of the variation of biopotential versus time. The electrical wave is generated by depolarization and repolarization of certain cells due to movement of Na+ and k+ ions in the blood. The ECG signal is typically in the range of 2 mV and requires a recording bandwidth of 0.1 to 120 Hz [1]. ECG is the process of recording the electrical activity of the heart over a period of time using electrodes placed on the skin. These electrodes detect the tiny electrical changes on the skin that arise from the heart muscle's electrophysiologic pattern of depolarizing and repolarizing during each heartbeat. It is a very commonly performed cardiology test.Find the cause of unexplained chest pain or pressure. This could be caused by a heart attack, inflammation of the sac surrounding the heart (pericarditis), or angina.Find the cause of symptoms of heart disease. Symptoms include shortness of breath, dizziness, fainting, and heartbeats that are rapid and irregular (palpitations).Find out if the walls of the heart chambers are too thick. It is detected and diagnosed by analysis of the recorded ECG waveform. The amplitude and duration of the P-QRS-T-U wave contains useful information about the nature of disease related to heart.

II. PROBLEM STATEMENT

The graph of voltage versus time produced by this noninvasive medical procedure is referred to as an **electrocardiogram**. The electrocardiogram is the most commonly known diagnostic biomedical signal. It is the graphical representation of the function of the human heart, and can be recorded easily with surface electrodes placed on the limbs and chest. To the trained clinician, an ECG conveys a large amount of information about the structure of the heart and the function of its electrical conduction system.[2] Among other things, an ECG can be used to measure the rate and rhythm of heartbeats, the size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, the effects of cardiac drugs, and the function of implanted pacemakers. In a clinical environment during acquisition, various types of artifacts get added to the ECG signal. There are various noise affects or get added in these Electrocardiogram signals at the time of taking signals from the body of the patient and change the original signal. So it becomes very important to remove the noise signal from electrocardiogram signals. Since biological signals are low amplitude and low frequency signals, they are easily prone to noise. Removing motion artifacts from an electrocardiogram (ECG) is one of the important issues to be considered during real-time heart rate measurements in telemetric health care. However, motion artifacts are part of the transient baseline change caused by the electrode motions that are the results of a subject’s movement. The word artifact is similar to artificial in the sense that it is often used to indicate something that is not natural (i.e. man-made). The predominant artifacts present in the ECG include: Power-line Interference and Baseline Wander. Power Line Interference: The power line interference of 50/60 Hz is the source of interference and it corrupt the recordings of Electrocardiogram (ECG) which are extremely important for the diagnosis of patients. The interference is caused by: a. Electromagnetic interference by power line b. electromagnetic field (EMF) by the machinery which is placed nearby. The signal component holds harmonics with different amplitude and frequency. The harmonics frequency is integral multiple of fundamental frequency such as 50Hz. c. Stray effect of the alternating current fields due to loops in the cables d. Improper grounding of ECG machine or the patient. e. Electrical equipments such as air conditioner, elevators and X-ray units draw heavy power line current, which induce 50 Hz signals in the input circuits of the ECG machine.

Baseline wandering occurs due to respiration.

In wandering baseline, the isoelectric line changes position.

One possible cause is the cables moving during the reading.

Patient movement, dirty lead wires/electrodes, loose electrodes, and a variety of other things can cause this as well. The distortions caused by electromagnetic wave can reduce by The simple electromagnetic shielding of cables and grounding of the chassis of the equipment. This artifact changes the morphology of the ECG signals, degrades the signal quality, and produces large amplitude signals that can resemble P-Q-R-S-T waveforms [3]. All these factors make few features which are important for the monitoring clinically and diagnosis of the heart disturbances.Mostly biological signals and power line interference are not related with each other so the solution of the above problem becomes difficult. So for better diagnosis it is important of the cancellation of these artifacts in ECG signals.The extraction of high-resolution ECG signals from recordings, which are perturbed by noise, is the significant matter. There is one big problem is denoising of the ECG signal.

The main objective of ECG signal denoising is to separate the desired signal components from the unwanted artifacts, so as to present an ECG that facilitates simple and accurate interpretation. Due to the overlapping between cardiac and non-cardiac components in frequency, especially from 0.01 Hz to 100 Hz, linear filtering (like low-pass or band-pass filter) is insufficient to eliminate such noises, by keeping the desired components unchanged. Clinically Real time automated ECG analysis, is of great assistance to experts in detecting heart disease, which often arise as a consequence of a heart disease and may be life-threatening and need immediate treatment. The main aim of this work is to denoise the ECG signal by developing different denoising methods.

The objective of this research work i.e. for denoising of the ECG signal using Wavelet based soft thresholding (Rigrsure) and Empirical Mode Decomposition (EMD) is to introduce the based automated system.As reference Premature Ventricular Contraction (PVC) and Fusion signals of the MIT-BIH Database are used. Using Signal-to-Noise Ratio (SNR) and Signal-to-Error Ratio (SER) the performance of proposed system is evaluated.

III. PROPOSED METHOD

Empirical Mode Decomposition (EMD)

In this method the noisy ECG signal is decomposed in to different intrinsic mode functions (IMFs)

Each IMF preserves the properties of the original signal in local time scale. An EMD essentially acts like a dyadic filter bank in time domain. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components. These components form a complete and nearly orthogonal basis for the original signal. In addition, they can be described as **intrinsic mode functions** (**IMF**).[1]

Because the first IMF usually carries the most oscillating (high-frequency) components, it can be rejected to remove high-frequency components (e.g., random noise).

An IMF is defined as a function that satisfies the following requirements:

1. In the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The total number of IMF components is roughly limited to $\log 2N$, where N is the total number of data points. It represents a generally simple oscillatory mode as a counterpart to the simple harmonic function. By definition, an IMF is any function with the same number of extrema and zero crossings, whose envelopes are symmetric with respect to zero.[6] This definition guarantees a well-behaved Hilbert transform of the IMF.

An EMD decomposes the original speech signal x(t) in to set of IMF through an iterative procedure called Sifting algorithm is given below.

Stepwise EMD algorithm can be described as follows:

Step 1: Initialize $-r0(t) = x(t), i = 1, ri(t) = r0(t)$

Step 2: Procedure to extract the *ith* IMF

- Initialize: $h0(t) = ri(t), J = 1$.
- Extract all the local minima and maxima of $hJ-1(t)$.
- Interpolate the local maxima and the local minima by a cubic spline to construct upper and lower envelopes of $hJ-1(t)$.

- Calculate the mean $mJ-1(t)$ of the upper and lower envelopes.
- $hJ(t) = hJ-1(t) - mJ-1(t)$
- If stopping criterion is satisfied then set $imfi(t) = hJ(t)$ else go to (b) with $J = J + 1$

Step 3: $ri+1(t) = ri-1(t) - imfi(t)$

Step 4: if $ri+1(t)$still has at least 2 extrema then go to 2 with $i = i + 1$ else the decomposition procedure ends. And $ri(t)$is the residue.

Finally, when EMD procedure is completed after n iterations the original signal can be reconstructed as:

$$(t)=\Sigma imf j+(t)nj=1 \quad (1)$$

Where $r(t)$ is the final residue which is a monotonic function which does not contain any frequency components and referred to as trend, set of mono-components represents the detail and n is the non-negative integer depends on $x(t)$.

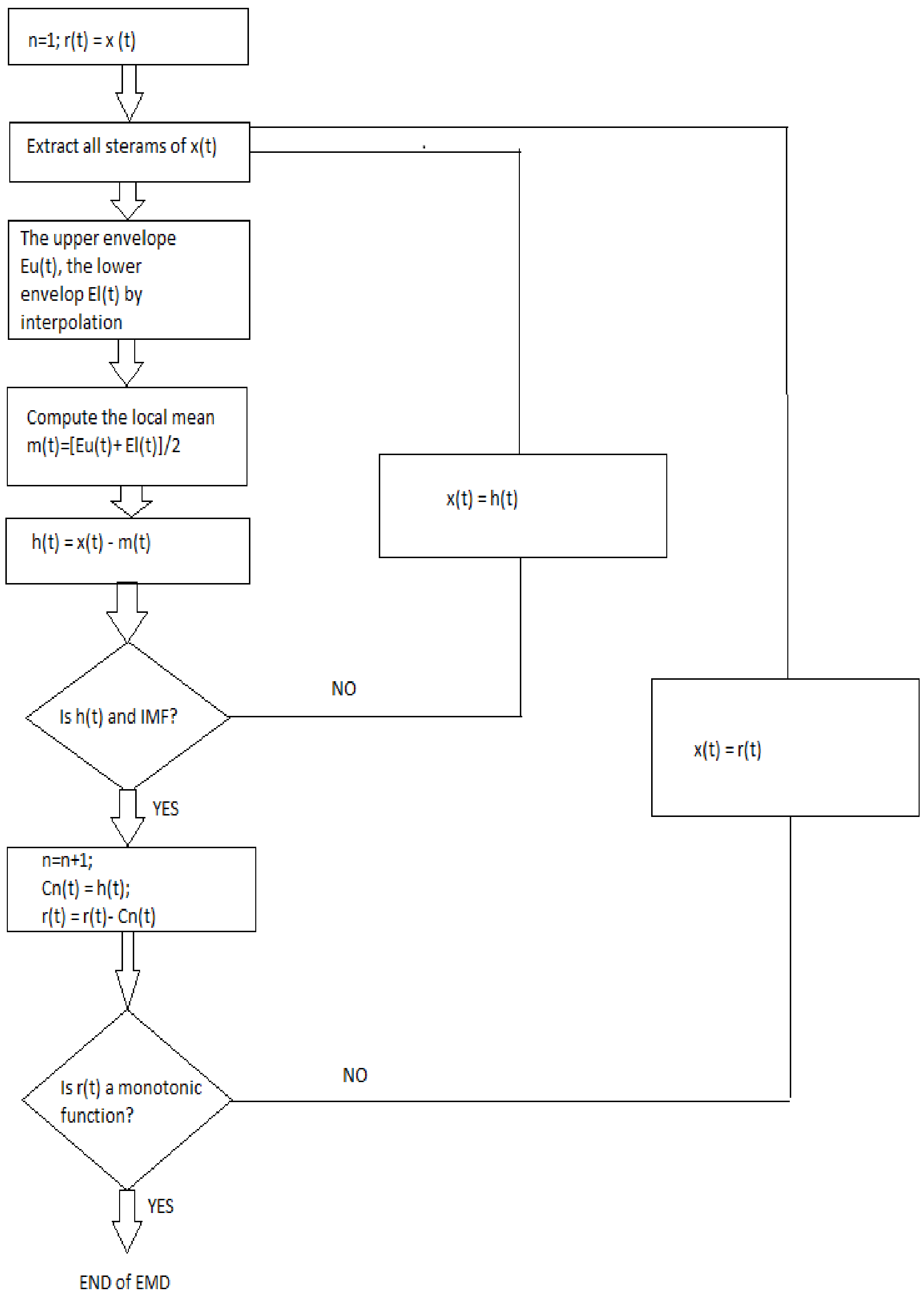

Figure 1: Empirical Mode Decomposition Flow-chart

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An example of the EMD implementation is shown in Figure 2. All the waveforms shown are the IMFs generated by the EEG signal. The last waveform is the residue. From the Figure 2 it can be inferred that as the algorithm progresses, the IMFs generated are of lower frequency than the previous ones.

Thus we adventure this property of EMD for our benefits by completely removing the IMF with maximum correlation and the IMFs generated thereafter.

Algorithm

1. Filter using notch filter at 50Hz, Butterworth high pass filter at 0.5Hz to eliminate the slow varying components and restrict to the frequency band 0.5Hz – 50 Hz. Then the trend from the signal is removed i.e. subtracting the mean from the signal.
2. Decomposition of EEG signal into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD).
3. Compute the cross-correlation between EOG signal and the individual IMFs.
4. Compute the energy of the output signals.
5. Eliminate the IMFs with high energy (correlation) and the IMFs generated thereafter.
6. Recombine the IMFs to form the EEG signal with reduced artifacts.

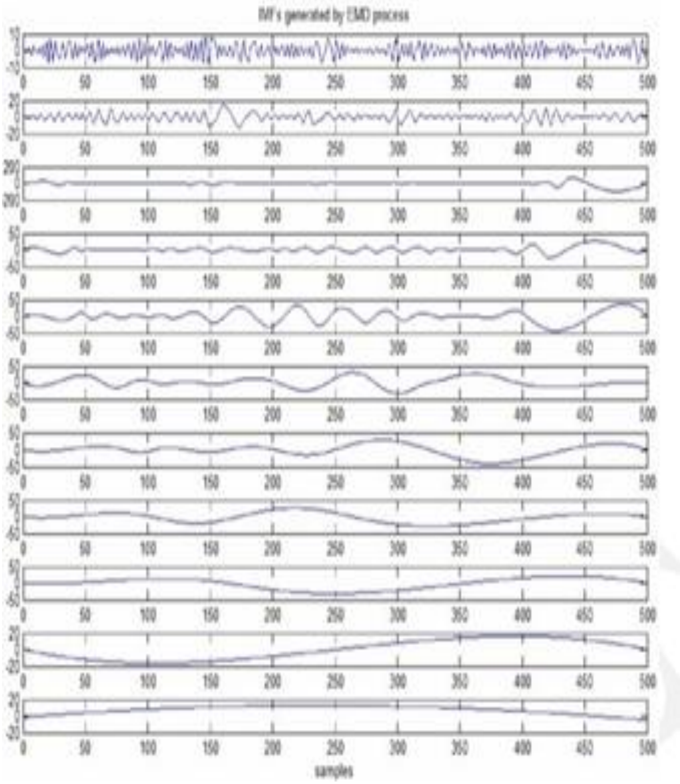

Figure 2: IMFs produced after from EEG signal after EMD

Discrete Wavelet Transform

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The continuous wavelet transform (CWT) of a signal $(x)\in L2(R)$ (Hilbert space) is an integral operation defined as:

$$(a,b)=1\sqrt{a}\int(x)\psi(x-ba)dx\infty-\infty \quad (2)$$

Where $w(a,b)$ are the wavelet coefficients, $\psi(x-ba)$ are the wavelets generated by a basic wavelet function $\psi(x)\in L2(R)$, the so-called the mother wavelet, a is the dilation parameter that scales the wavelet function by compressing or stretching it, and b is the translation parameter that locates the position of the wavelet function by shifting it. It is seen from this definition that the wavelet transform is a linear operation. By changing the variable $x = ax'$ and expressing the dilation parameter as $a = a1$, where $a1$ and vj (j=1, 2, 3,…) are real numbers then equation (2) becomes,

$$(a1vj,)=\sqrt{a1vj}\int(a1vjx')\psi(x'-ba1vj)dx'\infty-\infty \quad (3)$$

Therefore, the wavelet transform can be seen as a decomposition of the signal $f(x)$ into a number of resolution levels with j = 1, 2, 3, ⋯. Figure 3 demonstrates a various levelled structure for the decomposition of a signal $f(x)$ into numerous determination levels of the wavelet transform. It is seen from this figure that, in order to obtain the wavelet coefficients $w(a1vj,b)$ of a certain resolution level j, the signal is first scaled by a factor of $a1vjj$, and then integrated with a dilated and translated wavelet function $\psi(x-ba1vj)$ trailed by a multiplication with the magnitude factor $\sqrt{a1vj}$. It is also seen from this figure that the wavelet transform is very suitable for analyzing the hierarchical structure of the function $f(x)$ because of its mathematical microscopic property that permits an indicator to be spoken to by various capacities with programmed adaptability.

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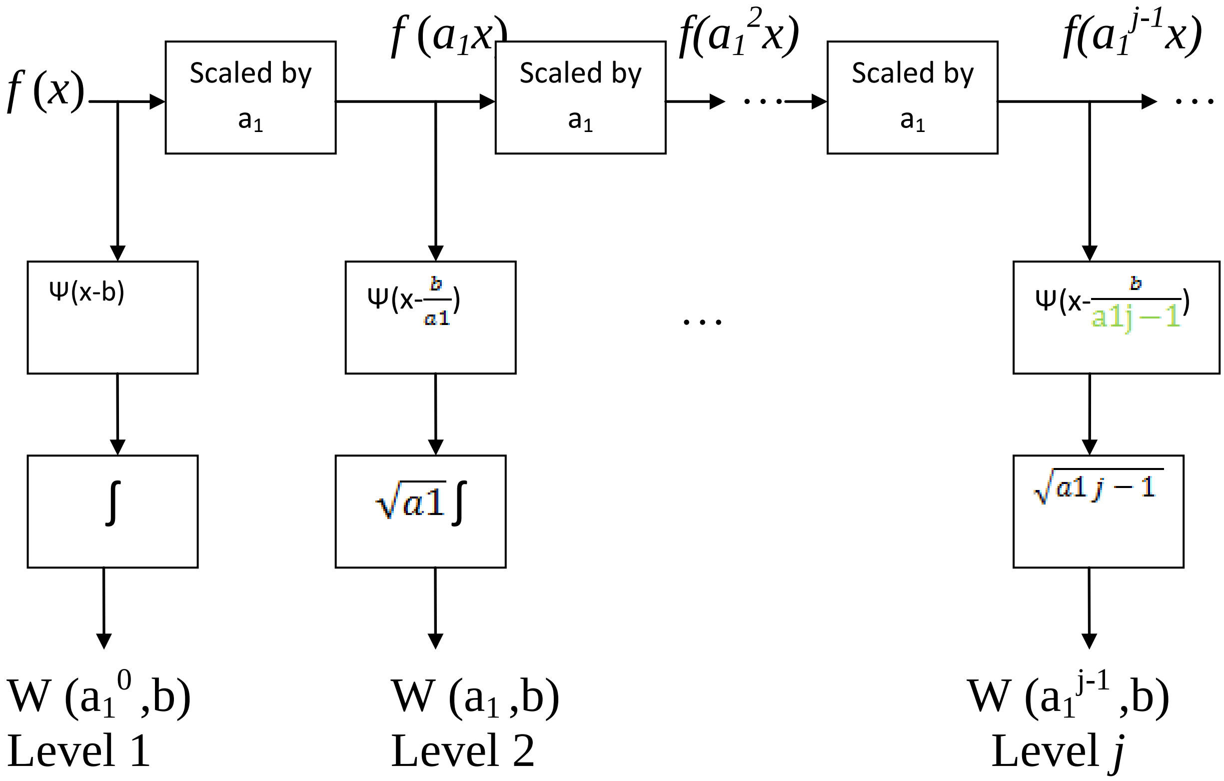

Figure 3: Hierarchical structure for the decomposition of a signal (x) into multiple resolution levels of the wavelet transform.

Proposed Wavelet Denoising Scheme

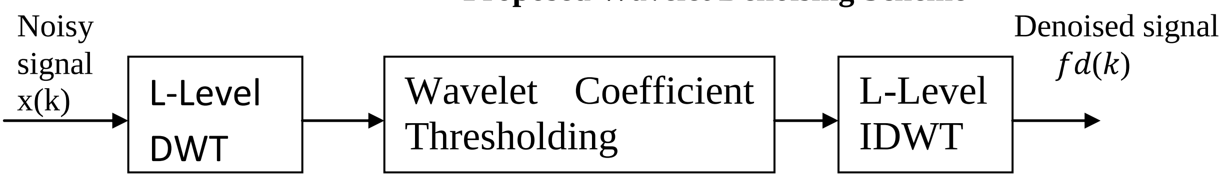

Figure 4: Wavelet Denoising Scheme

To stop downturn in value of instrumental signals, there is need of denoising of the signal. Let us suppose an instrumental signal (k) is corrupted by the noise (k) as (k) = (k) + (k), where (k) is White Gaussian Noise. It becomes tough to get rid of White Gaussian noise as it is located at all frequencies. The wavelet based overall denoising scheme is shown in Figure 4.

- From Figure 4, it is found that there are three main steps in the denoising scheme,
- L-level Inverse Wavelet Transform for reconstruction of denoised signal.
- Threshold estimation and thresholding of wavelet coefficients.
- L-level Wavelet Decomposition of input noisy signal.

Coefficients below a specific threshold value are set to zero in Wavelet denoising which involves thresholding. It becomes very helpful in reducing noise but the important characterstics of the original signal are preserved.Hard thresholding sets any coefficient less than or equal to the threshold to zero.

While Soft- Thresholding set the wavelet coefficients to zero which are below threshold as well as it simply shrinks or scales other coefficients which are above the threshold value. How to select Threshold is very important procedure which directly reflect the output quality of denoised signal

There are many lnown threshold evaluation, methods available in literature.

In this research work, performance of Rigrsure threshold estimation method is investigated for ECG signals corrupted by Additive White Gaussian Noise.

Rigrsure Tresholding

It is a soft threshold evaluator of unbiased risk. Suppose W = $w1$, $w2$, … , wN is a vector consists of the square of wavelet coefficients from small to large. Select the minimum value rb $(bthr)$ from risk vector, which is given as the risk value:

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$R = \{ \}$=1,2,…,N = [N−2i+(N−i)wi+Σ wk lk=1] N (4)
The selected threshold is $\lambda = \sigma\sqrt{wb}$ where, wb is the bth squared wavelet coefficient (coefficient at minimum risk) chosen from the vector W and σ is the standard deviation of the noisy signal.

IV. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.

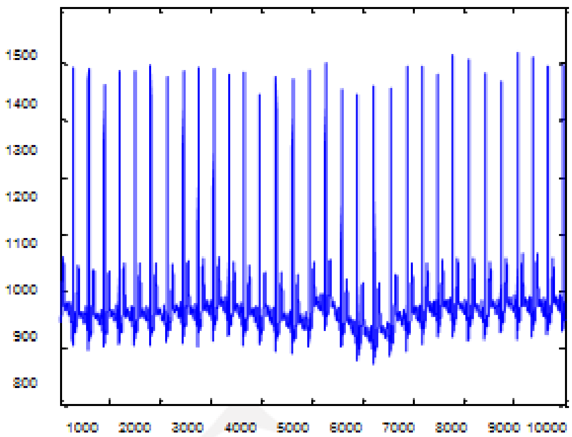

Figure 5: Original Signal

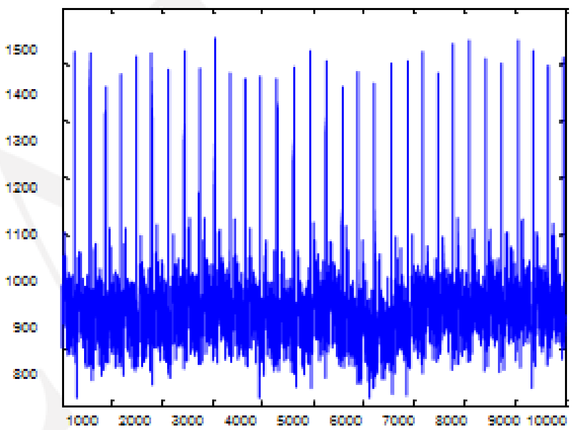

Figure 6: Signal with noise

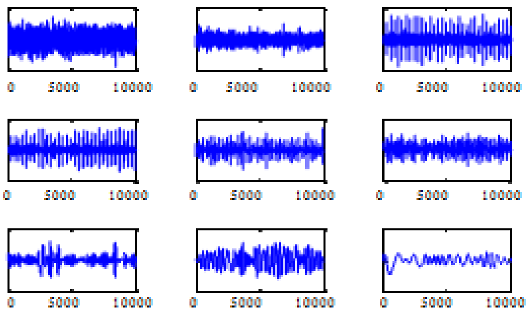

Figure 7: Intrinsic Mode Functions

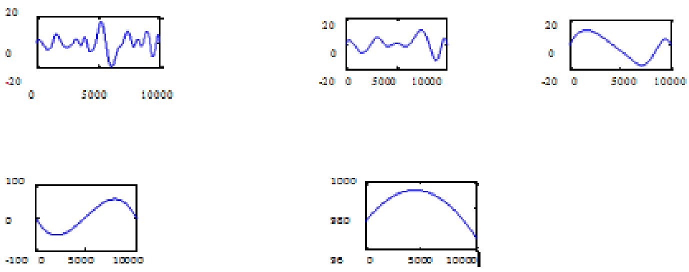

Figure 8: Intrinsic Mode Functions

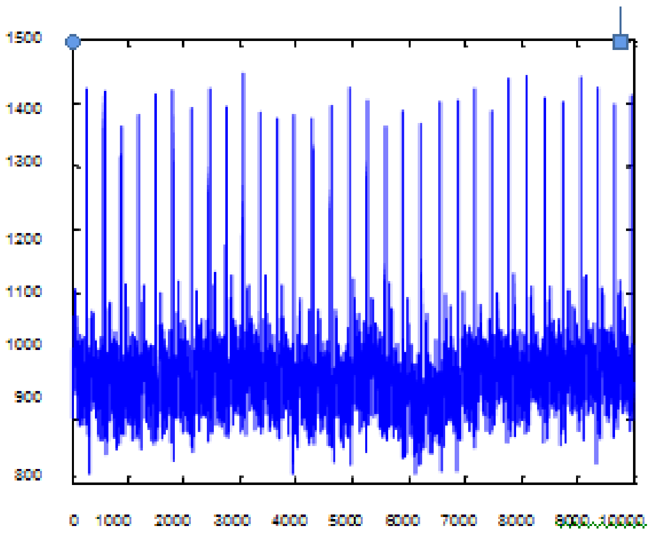

Figure 9: Denoised signal at low SNR

Table 1: Experiments carried out for the several records from MIT–BIH Arrhythmia database for Additive White Gaussian Noise (AWGN)

SNR (dB)	SER for ECG Record 100	SER for ECG Record 103	SER for ECG Record 105	SER for ECG Record 119	SER for ECG Record 212
6	34.73	29.64	30.017	24.14	29.60
8	36.73	31.6462	32.0176	26.15	31.60
10	38.74	33.6491	34.0192	28.14	33.630
12	40.74	35.6456	36.0212	30.146	35.6412
14	42.73	37.6401	38.12	32.14	37.675
16	44.70	37.6382	40.015	34.1456	39.6188
18	46.6932	41.6357	42.0085	36.1468	41.6076

V. CONCLUSION

Denoising of ECG signals could be very important in clinical usage and lead to early detection of a fairly common disease and could help contribute to reduced death. In this paper, the use of Empirical Mode

Decomposition and Discrete Wavelet Transform for denoising of the ECG beats is presented. The denoising process rejects noise by thresholding in the wavelet domain. Discrete wavelet transform has the benefit of giving a joint time frequency representation of the signal. Also it is suitable for both stationary and non-stationary signals and is the most appropriate system in the field of signal detection. The data is compared with MIT-BIH database and it was found that proposed “rigrsure” method gives optimum performance. Future work may be directed on the use of soft computing techniques. Tresholdig could be accomplished by any soft computing method rather than “rigrsure” based soft thresholding.

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