A Study on Enhancement Techniques For Electrocardiogram Signals

Thesis submitted in partial fulfillment

of the Requirements for the degree of

Master of Technology

in

Communication and Signal Processing

by

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Rourkela, Odisha, 769 008, India
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Under the guidance of

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Department of Electronics and Communication Engineering
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2012

Dedicated to My Parents

Department of Electronics and Communication Engineering
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Certificate

This is to certify that the work in the thesis entitled **"A Study on Enhancement techniques for Electrocardiogram signals"** by **Anil Chacko** is a record of an original research work carried out by him during 2011 - 2012 under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology with the specialization of Communication and Signal Processing in the department of Electronics and Communication Engineering, National Institute of Technology Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Place: NIT Rourkela
Date: 1 June 2012

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Finally, I humbly bow my head with utmost gratitude before the God Almighty who always showed me the path to go and without whom I could not have done any of these.

Anil Chacko

Contents

Abstract

Electrocardiogram (ECG) is a noninvasive technique that is used as a diagnostic tool for cardiovascular diseases. During the acquisition and transmission of ECG signals, different noises get embedded with it such as channel noise, muscle artifacts, electrode motion and baseline wander. In this project two techniques for ECG enhancement is proposed. The first method is based on Empirical Mode Decomposition and second method is based on time-frequency domain filtering using S-Transform. The performance of both techniques is compared with commonly used Wavelet Transform (WT) ECG enhancement technique.

In EMD based ECG enhancement technique, the noisy ECG signal is initially decomposed into a set of Intrinsic Mode Functions (IMFs). In this method, the IMFs which are dominated by noise are automatically determined using Spectral Flatness (SF) measure and then filtered using butterworth filters to remove noise. This method gives good performance with high SNR and lower RMSE for channel noise. However, the method fails to provide signal enhancement for other types of noises.

In S-Transform based enhancement technique, noisy ECG signal is represented in time-frequency domain using S-Transform. Next, masking and filtering technique is applied to remove unwanted noise components from time-frequency domain. This method gives good performance with high SNR and lower RMSE for different noises that are more probable to get embedded with ECG signal during its acquisition and transmission.

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List of Abbreviations

ECG	Electrocardiogram
MIT-BIH	Massachusetts Institute of Technology - Beth Israel Hospital
WT	Wavelet Transform
ST	Stockwell Transform (S-Transform)
TFR	Time Frequency Representation
SNR	Signal to Noise Ratio
RMSE	Root Mean Square Error
MA	Muscle Artifacts
EM	Electrode Motion
BW	Baseline Wander

1 Introduction

1.1 ECG

Electrocardiography (ECG) is a noninvasive technique that shows the electrical activity of the heart [1]. This is achieved by placing electrodes on the skin at specific points on the body. Since the electrical activity is directly correlated to heart functioning, it can be used to inspect the regularities and rate of heart rhythms. Therefore any change in heart rhythm caused by cardiac arrhythmias will reflect in the person's ECG also [2]. In General, ECG provides following information [3]

- Position of the heart and the size of the chambers
- Origin of impulse and its propagation
- Heart rhythm, Heart rate and disturbances in conduction
- Variations in electrolyte concentrations
- Position of myocardial ischemia

Hence ECG is widely used as a diagnostic tool by physicians throughout the world to analyze the hearts condition.

Heart muscles generally have a negative polarity and when this negative polarity charge becomes zero, it can be said that the heart muscle is depolarized [2]. During a cardiac cycle, a wave of depolarization occurs which results in the contraction of atria and ventricles which constitute a heart beat. ECG detects these tiny changes of electric charges that is displayed on a monitor or printed on a graph paper [4].

1.2 Anatomy of Heart

The heart is the central part of the cardiovascular system of human body [1]. Cross section of the human heart is shown in Fig. 1.1 [4]. The arteries carry blood from the heart to different parts of the body and the veins carry the blood from all parts of the body back to the heart. The heart consists of four chambers: The top

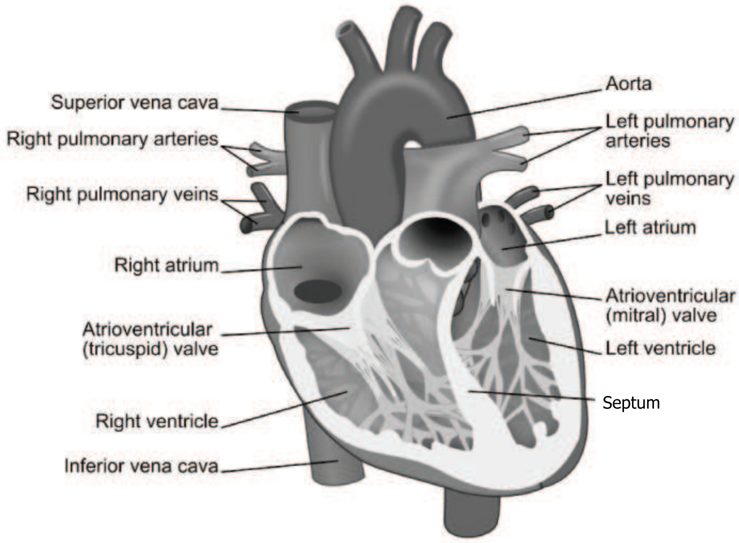

Figure 1.1: *Cross section of human heart [4]*

two chambers are called atria and the bottom two chambers are called ventricles. The atria and ventricles are separated by A-V valves.

The right atrium and right ventricle circulate blood between the heart and lungs. The oxygen poor blood from the veins flows to the right atrium through the superior venacava and inferior venacava. When the right atrium contracts this blood flows to the right ventricle through the tricuspid A-V valve. The right ventricle then pumps the blood from the hear to the lungs through left pulmonary artery. The blood gets oxygenated at the lungs [5].

The left atrium and the left ventricle circulate the oxygen-rich blood between the heart and rest of the body. The oxygenated blood from the lungs flow to the left atrium through the left pulmonary veins. When the left atrium contracts the blood is pumped to the left ventricle through the mitral valve. The left ventricle pumps this blood to rest of the body through the aorta [5].

1.3 Leads in ECG

A lead is a particular "view" of the electrical activity of the heart which are obtained by a pair of electrodes placed on designated location on the human body [4]. The standard ECG has 12 leads which belongs to the following three

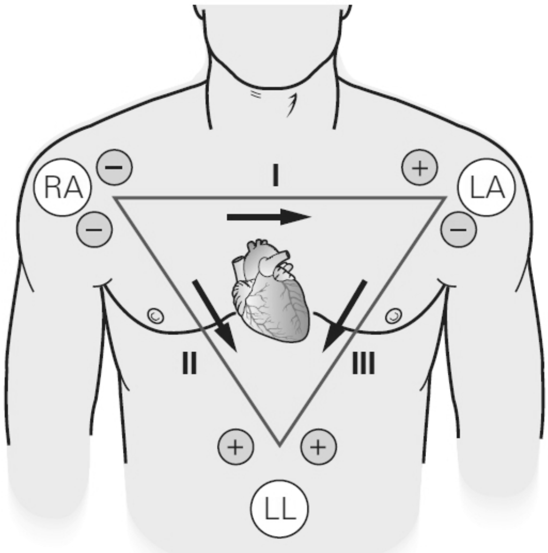

Figure 1.2: *Leads I, II and III [6]*

classes

1.3.1 Bipolar Leads

These leads are obtained with electrodes of opposite polarity (+ve and -ve) [6]. Leads I, II and III belong to this category.

- Lead I : Difference between left arm (LA) electrode potential and right arm (RA) electrode potential (LA-RA).
- Lead II : Difference between left leg (LL) electrode potential and right arm (RA) electrode potential (LL-RA).
- Lead III : Difference between left leg (LL) electrode potential and left arm (LA) electrode potential (LL-LA).

1.3.2 Unipolar Leads

These leads are obtained with a single positive electrode and a reference point that lies in the center of heart's electric field. Leads aVR, aVL and aVF are unipolar limb leads [6].

- Augmented Vector Right (aVR): The potential difference between right arm electrode and the center of heart's electric field

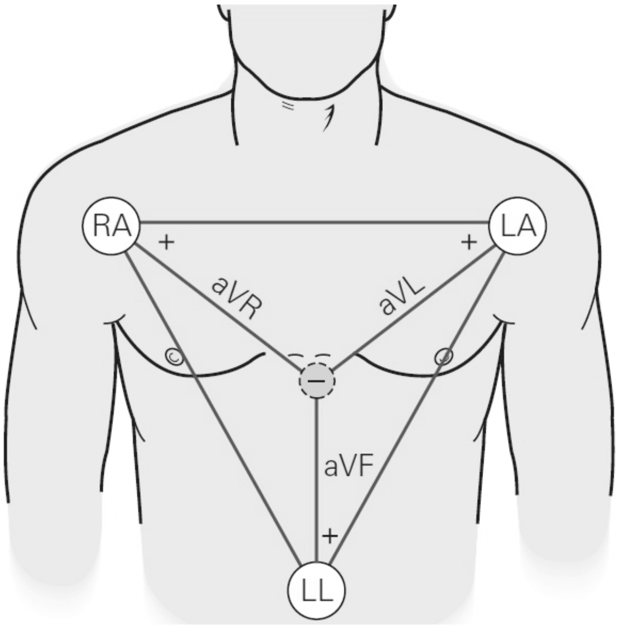

Figure 1.3: *Unipolar limb leads [6]*

- Augmented vector left (aVL): The potential difference between left arm electrode and the center of heart's electric field.
- Augmented vector foot (aVF): The potential difference between left leg and the center of the heart's electric field.

Leads V1-V6 are unipolar chest leads. Here the positive electrodes of leads V1-v6 is placed at specific points on the chest as shown in the Fig. 1.4. The leads show the potential difference between the positive electrode and the center of the heart's electric field [6]. The location of the positive electrodes for V1-V6 leads is given below

- V1: Fourth intercostal space in right side of sternum.
- V2: Fourth intercostal space in left side of sternum.
- V3: Directly between V2 and V4.
- V4: Fifth Intercostal space on the left midclavicular line.
- V5: In the same level of V4 at anterior axillary line on the left side.
- V6: In the same level of V5 at midaxillary line on the left side.

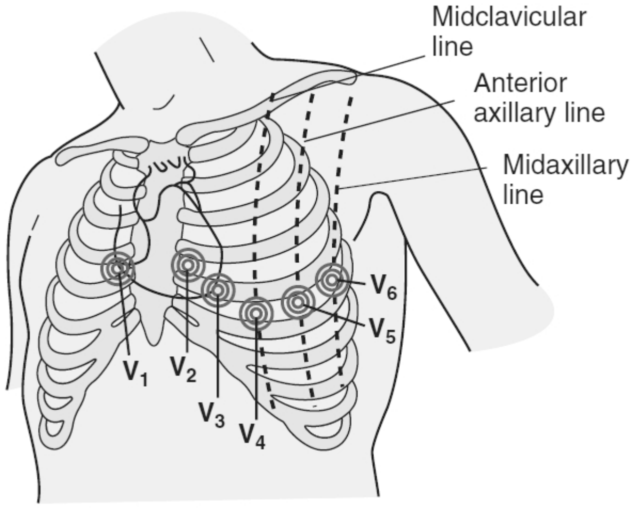

Figure 1.4: *Unipolar chest leads [6]*

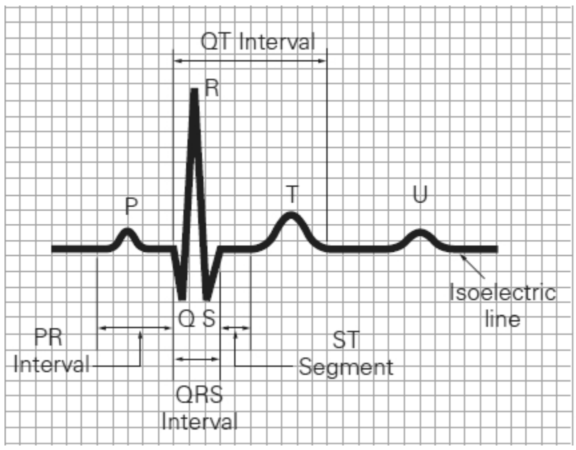

Figure 1.5: *ECG wave pattern for one cardiac cycle [6]*

1.4 ECG wave pattern

ECG wave for one cardiac cycle is shown in the Fig. 1.5. In general one cycle ECG signal consists of a P wave, a QRS complex, a T wave and U wave which is visible sometimes. The baseline voltage, known as isoelectric line, is considered as the line tracing from T wave to the next P wave [4].

- P wave: First wave seen and indicates depolarization of atria [2]. During this time the electrical impulse starts from SA node to AV node spreading through both the atria. The amplitude of this signal is approximately 1mV.

- QRS complex: This indicates the depolarization of the ventricles. QRS complex consists of three peaks: Q and S are negative peaks and R is the positive peak. It is the largest voltage deflection of around 10-20mv and has a duration of 80 - 120 ms [4].

- PR Segment: This is the time duration between the outset of the P wave to the outset of QRS complex. During this time, the electrical impulse travels from the atria to the ventricles through the AV node [6].
- T wave: This is a positive deflection soon after the QRS complex and indicates repolarization of the ventricles [3].
- ST Segment: This is the time duration between S wave and the outset of T wave and occurs between the depolarization and repolarization of ventricles. ST segment always align with the isoelectric line [6].
- U wave: It is a small deflection following T wave and represents the repolarization of purkinje fibres [6].

1.5 Noises in ECG

Different kinds of noises can affect ECG signal during its acquisition and transmission [7]. These noises can corrupt the ECG signal and hence analysis of ECG becomes very difficult. The probable types of noises that affect ECG are given below

1.5.1 Muscle Artifacts

Muscle artifacts are also known as Electromyography (EMG) noise. These noises occur due to the muscle activity during ECG acquisition especially during a stress test [7]. Muscle artifacts are assumed to be transient bursts of gaussian noise and is band limited and have zero mean. Burst duration can be upto 50ms with a maximum frequency of 10 KHz [8].

1.5.2 Electrode Motion

Electrode motion or motion artifacts occur due to the shift in the electrode position during exercise ECG [7]. The motion of electrodes can introduce a higher amplitude signal in the ECG signal. Generally it can have a duration of 100-500ms [8]

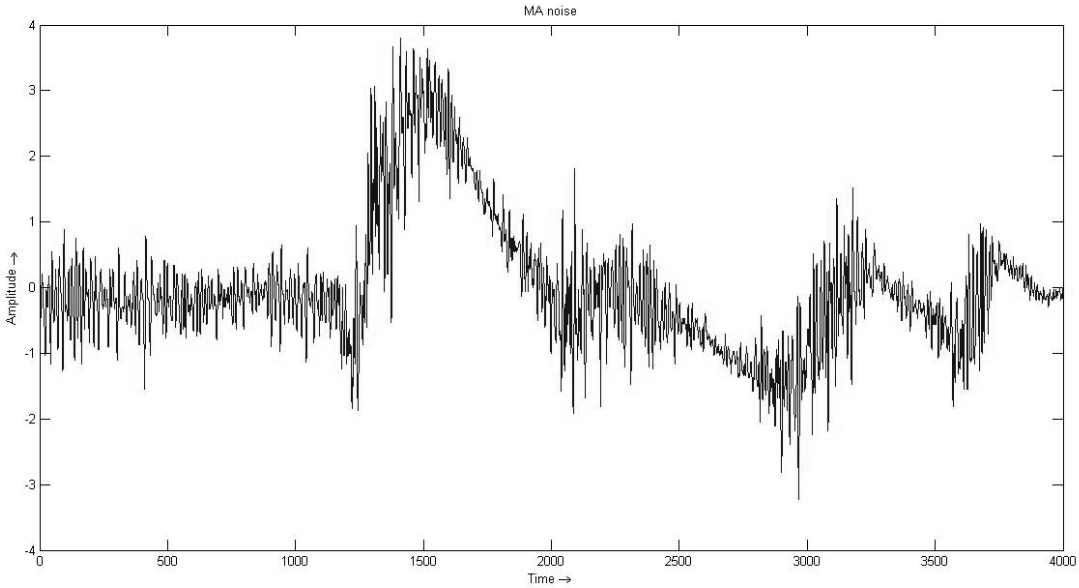

Figure 1.6: *Muscle Artifacts noise*

and have frequency components overlapping with the frequency contents of the ECG signal.

1.5.3 Baseline wander

Baseline wander is the variation in the isoelectric line of the ECG signal. This usually occurs due to respiration or cough which causes in a large movement of chest for a chest-lead ECG and movement of arm or leg for a limb-lead ECG [9]. Effect of temperature and bias variations on the instruments and amplifiers can also cause drift in ECG baseline voltage. This is generally a low frequency signal with a frequency range of 0-0.5 Hz [10].

1.5.4 Channel noise

Poor channel conditions can also introduce noise to ECG when ECG is transmitted. Usually it is modeled using white gaussian noise which contains all frequency components [7].

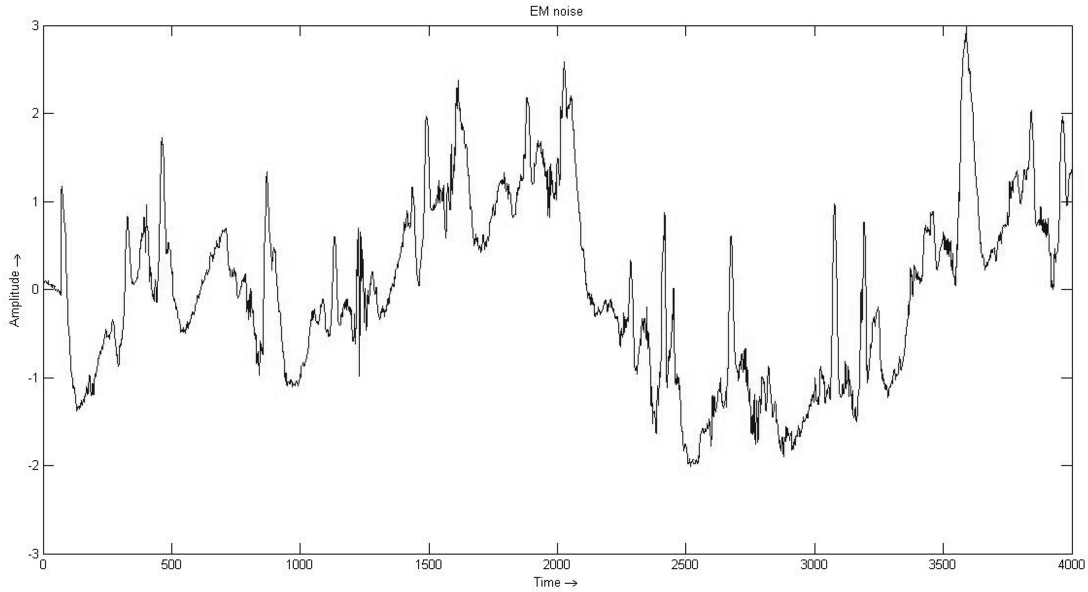

Figure 1.7: *Electrode Motion noise*

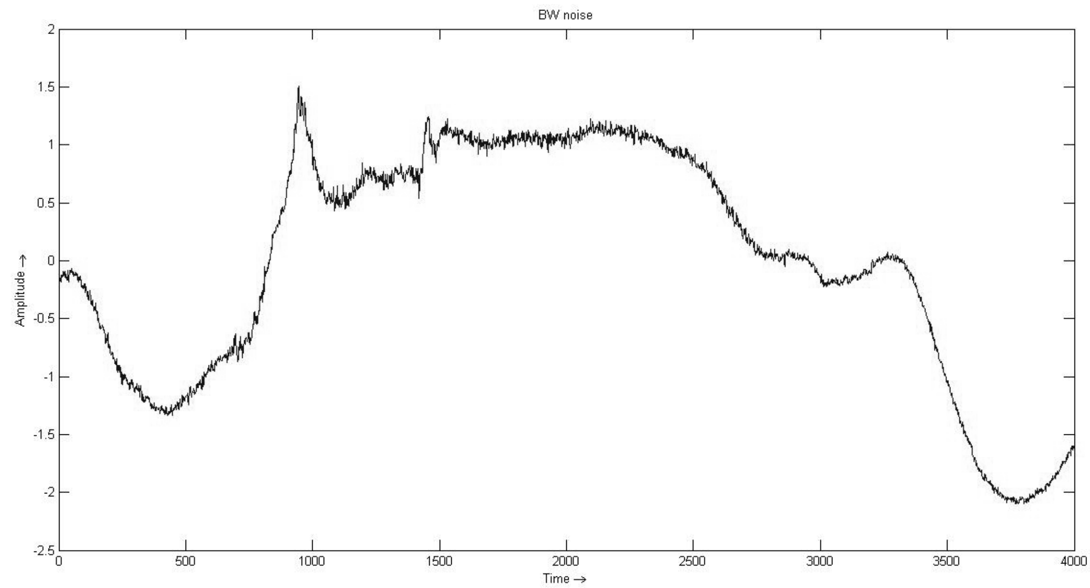

Figure 1.8: *Baseline Wander noise*

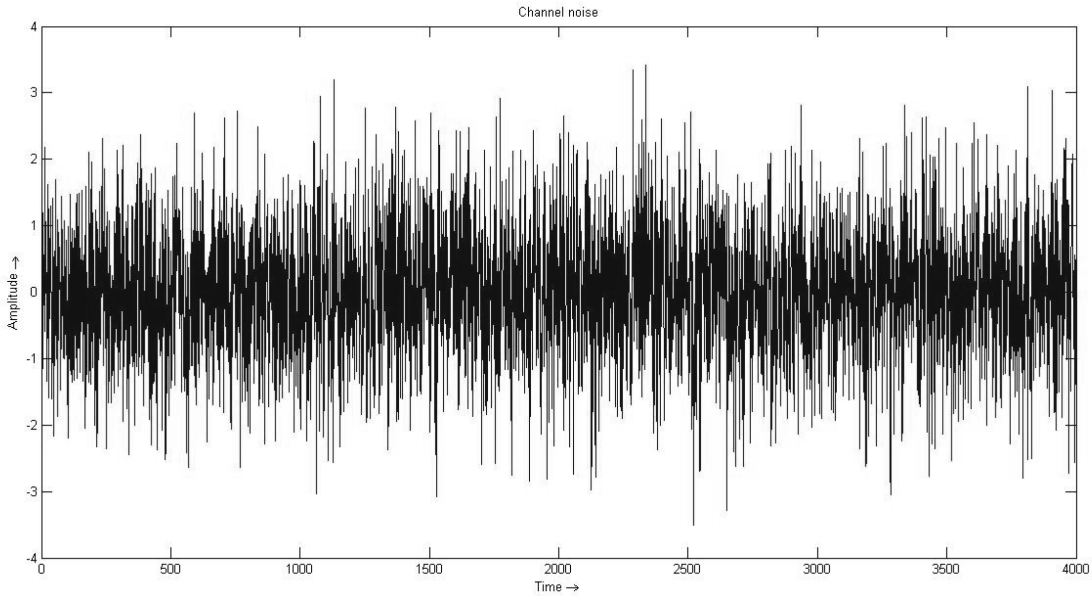

Figure 1.9: *Channel noise*

1.6 ECG Database

1.6.1 MIT-BIH Arrhythmia Database

MIT-BIH Arrhythmia database is setup by Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (BIH) to conduct research on arrhythmia analysis and other cardiac dynamics [9]. This repository was made open to others from 1980 and was made available online in September 1999. Henceforth these datas have been used by researchers worldwide for their research and analysis. The database consists of 48 different records each having a duration of 30 minutes. All these records have a sampling frequency of 360Hz and have 2 channels comprising of lead II and lead V1 [9]. Each beat in these records are properly annotated by a set of expert cardiologists.

1.6.2 MIT-BIH Noise Stress Test Database

This database includes 3 recordings of noise that usually appear during ECG recordings such as baseline wander, muscle artifact and electrode motion. These recordings are taken from physically fit volunteers and standard recorders and instruments. The electrodes are placed on different positions on the body where ECG signal is not available [11].

1.7 Motivation

ECG reflect the condition of the heart and hence any abnormal heart condition will also appear as irregularities in the signal. However, these irregularities might not be consistent and hence it can be very tedious even for a trained physician to do a proper diagnosis. Therefore, researchers throughout the world are working on computational techniques that can assist in accurate analysis of ECG signal. However, different noises that get embedded with ECG signal during its acquisition and transmission can cause a great deal of hindrance to manual and automatic analysis of ECG signal. Therefore preprocessing has to be done to enhance the signal quality of ECG signal for further processing. Many techniques are reported in the literature for ECG denoising. Many of these techniques assume that prior information of the signal or type of noise is available. However, in practical scenario, it is not possible to obtain information of the signal or noise before processing. This situation has motivated me to study and implement enhancement techniques for ECG signal that can be applied for practical scenario where prior information is not available. In this project, two novel approaches using EMD and S-Transform are implemented and results are analyzed and compared with conventional techniques.

1.8 Thesis Outline

Chapter 1 of the thesis gives brief introduction to ECG and its wave pattern, ECG acquisition and different types of noise that can affect ECG

Chapter 2 explains ECG enhancement technique using Empirical Mode Decomposition (EMD). The Theoretical background of EMD is briefly outlined the proposed method is explained with results and comparison.

Chapter 3 discusses ECG enhancement technique using S-Transform. The proposed methodology is explained stage by stage and the output results are analyzed and compared.

Chapter 4 gives the conclusion and future work of the thesis.

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2
EMD based enhancement technique

2.1 Introduction

Many denoising techniques have been reported in the literature for ECG denoising such as adaptive filtering [1], statistical techniques like independent component analysis [2], fuzzy multiwavelet denoising [3] and wavelet denoising [4]. The wavelet based technique is more popular and shows better performance than the earlier methods [4]. Daubechies-4 (dB4) wavelet with soft thresholding shows the best performance among all wavelet families. Wavelet transform have been widely used for denoising of ECG signal because of its ability to characterize time frequency information where two types of thresholding are used to enhance the ECG signal. However, the wavelet transform technique has following limitations for application as a denoising method for ECG signal: (i) the hard thresholding may lead to the oscillation of the reconstructed ECG signal (ii) Soft thresholding method may reduce the amplitudes of the ECG waveforms and especially reduce the amplitudes of the R waves which is more important to diagnose the heart diseases [5].

Therefore, many researchers use Empirical Mode Decomposition (EMD) based denoising technique [6]- [7]. EMD decomposes a signal into few oscillatory functions known as Intrinsic Mode Functions (IMFs). Most of the denoising methods based on EMD technique follows partial reconstruction of the signal by removing noisy IMFs [6], [7]. However, this method removes the signal information along with noise. Here, a method for ECG denoising based on EMD is proposed, where noisy IMFs are automatically determined based on the Spectral Flatness (SF) measure. The noisy IMFs are then filtered to remove the noise components of the signals. Performance of this algorithm is tested on MIT-BIH arrhythmia database and evaluated based on Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE). The results are compared with the Wavelet Transform based denoising technique.

2.2 Theoretical Background

Empirical mode decomposition (EMD) was introduced by Huang *et al* [11] for decomposing a given signal $x(t)$ into a finite number of sub components called Intrinsic Mode Functions (IMFs). The IMFs represent the oscillatory mode of a particular signal and is obtained by a systematic process called *sifting*. An IMF should satisfy the following two properties.

1. The maximum difference between the number of extrema and the number of zero crossings should be 1.

2. At any given point, the mean of the envelopes created by the maximas and minimas should be 0.

The algorithm for performing sifting on a given signal $x(t)$ is given below

(i) Identify all the maximas and minimas of $x(t)$.

(ii) Interpolate between minima, ending up with a signal $x_{min}(t)$ and similarly between maximas to give $x_{max}(t)$

(iii) Calculate the average between those two envelopes:

$$x_{avg}(t) = (x_{max}(t) + x_{min}(t))/2 \tag{2.1}$$

(iv) Extract the detail: $d_1(t) = x(t) - x_{avg}(t)$. $d_1(t)$ is given as input to the next iteration of sifting.

A stopping criterion to the number of sifting iterations is employed to ensure that the IMF component retain enough physical sense of both amplitude and frequency modulation. This is by limiting the Standard Deviation (SD) between two consecutive sifting iteration results. If k number of sifting iterations are performed, then the SD is given by

$$SD = \sum_{t=0}^{L-1} \left[\frac{|d_{k-1}(t) - d_k(t)|^2}{d_{k-1}^2(t)} \right] \tag{2.2}$$

Typically the value of SD is set between 0.2 and 0.3.

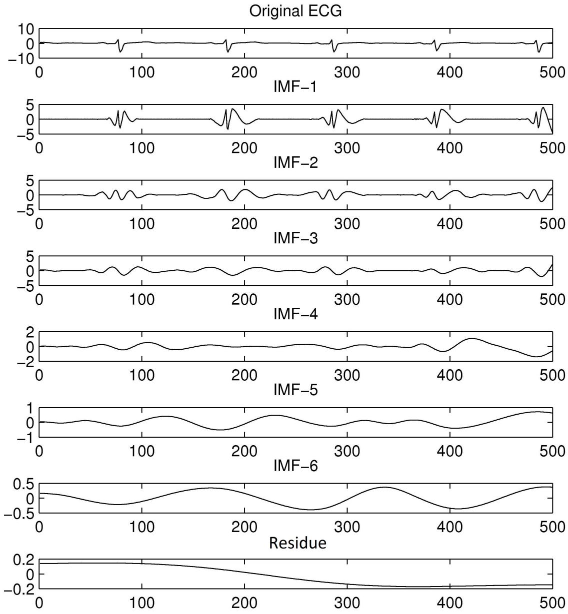

Figure 2.1: *The original ECG and its seven IMFs*

Once $d_k(t)$ is accepted as first IMF, $h_1(t)$, the residue is calculated as

$$r_1(t) = x(t) - d_k(t) \tag{2.3}$$

$$h_1(t) = d_k(t) \tag{2.4}$$

$r_1(t)$ is given as the input to the next round of sifting process to extract second IMF. The EMD process can be stopped when the residue $r(t)$ becomes a monotonic function from which no more IMF can be extracted.

If N rounds of sifting process is performed on the given signal $x(t)$, it will be decomposed to a set of N IMFs and a residue signal which can be denoted as

$$x(t) = \sum_{k=1}^{N} h_k(t) + r_N(t) \tag{2.5}$$

The above equation shows that a signal which is decomposed by EMD can be recreated easily by simple addition of the IMF components $h_k(t)$ and the residue signal $r_N(t)$. The decomposition of an ECG signal using EMD is shown in Fig. 2.1.

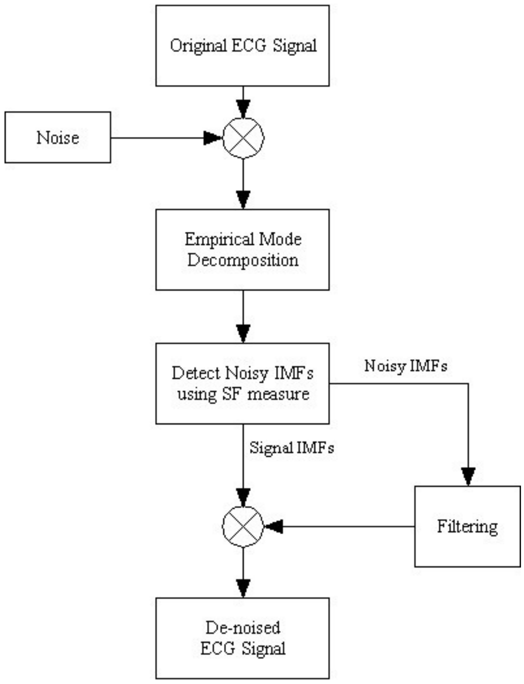

Figure 2.2: *Block diagram of EMD based ECG enhancement method*

2.3 Methodology

When a noisy signal is decomposed using EMD, the noise components are mainly present in the initial IMFs [12]. In this work, Spectral Flatness (SF) measure is used to determine whether a particular IMF is dominated by noise or not. Since the bandwidth of ECG is usually in the range from 0.05 to 100 Hz [13], the power spectrum of signal IMFs will be concentrated on a short range of frequencies. The spectrum of noisy IMFs will be relatively flat compared to signal IMFs.

The proposed noise removal method using EMD is illustrated in Fig. 2.2 and the different steps are explained below

Step 1: The ECG signals are taken from MIT/BIH arrhythmia data base [14]. Every file in the data base consists of two lead recordings sampled at 360 Hz sampling frequency with 11 bits per sample of resolution. The noisy signal $s(t)$ is obtained as $s(t) = x(t) + n(t)$ where $x(t)$ is the original ECG and $n(t)$ is the noise signal.

Step 2: The noisy ECG signal is decomposed into IMFs using EMD method.

Step 3: The number of noisy IMFs, n, is obtained by comparing the Spectral

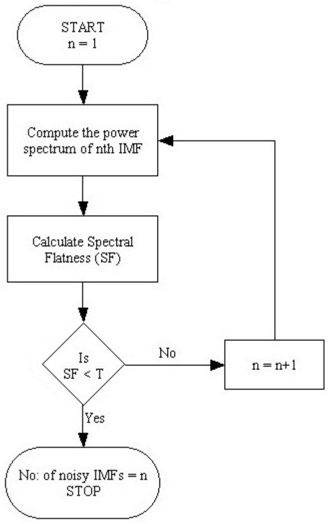

Figure 2.3: *Method to find out the number of noisy IMFs*

Flatness (SF) of each IMF to a threshold T. The Spectral flatness is calculated as the ratio of geometric mean of the power spectrum to its arithmetic mean [15]. It is given as

$$\text{Spectral Flatness} = \frac{\sqrt[L]{\prod_{n=0}^{L-1} H(n)}}{\frac{\sum_{n=0}^{L-1} H(n)}{L}} \tag{2.6}$$

The first n IMFs whose Spectral Flatness is above the threshold T are considered as noisy IMFs. This method is explained in Fig. 2.3. The threshold value of spectral flatness, T, is taken as 0.09 based on the experiments done on the database.

Step 4: Since significant part of the high frequency content of ECG is in the range of 40-60 Hz [12] the 1^{st} IMF is filtered using a bandpass butterworth filter of order 10 with pass band of 40-60 Hz. The remaining noisy IMFs are filtered using low pass butterworth filter of order 10 with cut off frequency of 60 Hz to extract the significant signal components.

Step 5: The ECG signal is reconstructed by adding the filtered IMFs and the remaining signal IMFs. The reconstructed signal $\hat{x}(t)$

$$\hat{x}(t) = \sum_{k=1}^{n} \tilde{h}_k(t) + \sum_{k=n+1}^{N} h_k(t) + r_N(t) \tag{2.7}$$

where $\tilde{h}_k(t)$ is the filtered version of $h_k(t)$

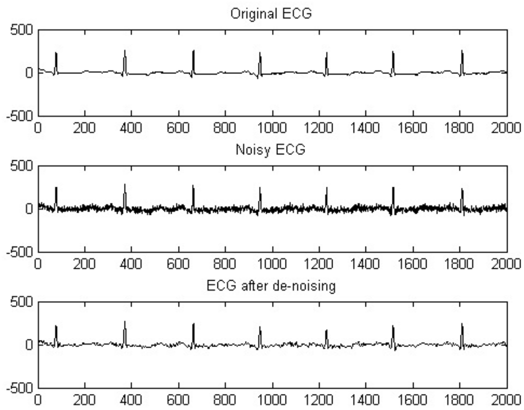

Figure 2.4: *Original ECG, Noisy ECG with 10 dB SNR and ECG with noise removed by EMD based enhancement technique*

2.4 Results and Discussion

The proposed algorithm is tested on MIT-BIH (Massachusetts Institute of Technology - Beth Israel Hospital) Arrhythmia database [14]. White Gaussian noise is added artificially to the ECG signals that results in 5dB, 10dB and 15dB SNR.

The performance of this method is evaluated based on the Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE) [16]. The SNR can be represented as the following

$$SNR = \frac{\sum_{t=0}^{L-1} x(t)^2}{\sum_{t=0}^{L-1} n(t)^2} \tag{2.8}$$

where $x(t)$ is the signal and $n(t)$ is the noise.

Here, RMSE is used to evaluate the quality of the information which is preserved in the denoised ECG signal. RMSE is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=0}^{L-1} (x(t) - \hat{x}(t))^2}{L}} \tag{2.9}$$

where the numerator part is the square error, $\hat{x}(t)$ is the reconstructed ECG signal and L is the length of the signal.

Fig. 4 shows the original ECG, noisy ECG and the denoised ECG using the proposed algorithm.

Table 2.1: *Experimental Results for EMD method and Wavelet based enhancement technique*

	5dB				**10dB**				**15dB**			
MIT/BIH	WT method		EMD method		WT method		EMD method		WT method		EMD method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
100	8.10	0.393	9.50	0.334	11.46	0.267	14.35	0.191	15.11	0.175	18.67	0.116
101	8.92	0.357	9.85	0.321	11.96	0.252	14.48	0.188	15.69	0.164	16.70	0.146
115	9.45	0.336	10.22	0.308	13.09	0.221	14.59	0.186	16.76	0.145	17.61	0.131
118	9.53	0.332	10.01	0.316	12.04	0.249	14.95	0.178	15.52	0.174	19.39	0.104
122	9.43	0.331	9.99	0.316	12.76	0.231	14.97	0.171	16.20	0.154	19.77	0.102
205	8.43	0.380	10.08	0.313	11.85	0.255	14.73	0.183	14.92	0.179	18.22	0.122
209	7.93	0.405	9.97	0.316	11.03	0.282	14.84	0.182	14.17	0.195	16.68	0.146
213	8.49	0.375	9.95	0.317	11.76	0.258	14.62	0.185	14.76	0.187	20.02	0.092
215	8.26	0.386	9.65	0.329	11.18	0.271	14.89	0.181	14.10	0.192	18.86	0.114
230	8.99	0.355	9.94	0.318	12.43	0.238	14.68	0.184	15.83	0.161	19.54	0.105

2.4.1 Experimental Results with Gaussian Noise

The Table 2.1 given shows the comparison of the SNR achieved by the proposed algorithm and the Wavelet Transform technique [4] for two different Input SNRs. The comparison values are given for 10 random sets of data picked from the MIT-BIH database. The average performance improvement of the proposed method is also shown.

2.4.2 Experimental Results with Real Case Noises

The proposed method was tested on ECG signals affected with real case noises such as Muscle Artifacts (MA), Electrode Motion (EM) and Baseline Wander(BW). Table 2.2 to Table 2.4 shows below the SNR and RMSE comparison. It can be seen that for real case noises, both WT based technique and proposed methodology fails as ECG enhancement techniques.

Table 2.2: *Experimental Results for Muscle Artifacts (MA) Noise*

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	5dB				**10dB**				**15dB**			
MIT/BIH	WT method		EMD method		WT method		EMD method		WT method		EMD method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
115	5.35	0.540	2.95	0.711	10.26	0.313	4.41	0.608	15.16	0.129	6.21	0.488
122	5.34	0.541	4.38	0.604	10.17	0.320	7.78	0.409	15.19	0.179	9.97	0.317
213	5.33	0.541	2.94	0.722	10.21	0.314	7.66	0.427	15.22	0.180	8.58	0.382
230	5.35	0.540	2.18	0.777	10.25	0.313	5.11	0.556	15.23	0.181	6.04	0.499

Table 2.3: *Experimental Results for Electrode Motion (EM) Noise*

	5dB				10dB				15dB			
MIT/BIH	WT method		EMD method		WT method		EMD method		WT method		EMD method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
115	5.01	0.562	2.58	0.742	10.09	0.322	5.67	0.520	15.01	0.171	4.89	0.569
122	4.98	0.563	4.17	0.618	10.01	0.327	8.50	0.376	15.02	0.172	9.61	0.311
213	4.98	0.564	3.02	0.706	10.02	0.327	4.72	0.580	15.08	0.173	10.64	0.294
230	5.00	0.562	2.99	0.708	10.07	0.325	4.44	0.487	15.10	0.173	6.25	0.487

Table 2.4: *Experimental Results for Baseline Wander (BW) noise*

	5dB				10dB				15dB			
MIT/BIH	WT method		EMD method		WT method		EMD method		WT method		EMD method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
115	4.98	0.564	1.87	0.805	10.00	0.327	3.26	0.637	15.08	0.173	5.78	0.154
122	4.95	0.565	4.503	0.595	9.98	0.328	9.44	0.337	15.01	0.171	11.18	0.275
213	4.96	0.585	3.02	0.711	9.97	0.329	4.67	0.504	14.99	0.170	10.31	0.305
230	4.98	0.564	3.36	0.679	10.01	0.327	2.68	0.383	15.07	0.172	8.32	0.384

2.5 Conclusion

An EMD based method for denoising of ECG signal is proposed. Automatic detection of noisy IMFs is done using spectral flatness measure. The noisy IMFs are filtered and then added with signal IMFs to obtain the denoised ECG signal. The proposed technique is evaluated on 5dB, 10dB and 15dB SNR where white gaussian noise is artificially added with original signal. Performance of the proposed method shows better SNR performance and lower RMSE for gaussian noise compared to Wavelet Transform based technique which is usually used as an ECG signal denoising technique. However, the proposed methodology fails to perform as an enhancement technique for real case scenario.

2.6 References

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3 S-Transform based enhancement technique

3.1 Introduction

During acquisition, ECG signals can be affected by different noises like muscle artifacts, electrode motion and baseline wander [1, 2], especially during a stress test. Muscle artifacts are introduced due to muscle activity and electrode motion is caused by the shift in electrode location. Baseline wander is the variation in iso-electric line of ECG which can occur during respiration. Poor channel conditions can also introduce noise in the ECG signal during its transmission [1]. All these noises can corrupt the signal thereby making its analysis difficult and error prone. Hence noisy ECG signals should be enhanced by removing the noise components for further processing.

Various techniques have been reported in the literature for enhancement of ECG signal [2–9] including techniques like fuzzy multiwavelet denoising [3], Independent Component Analysis [4], wavelet denoising [5] and Least Mean Square (LMS) algorithm based adaptive filter [2]. However, most of these reported techniques generally concentrated only on one kind of noise type [3–9]. Few reported techniques [1, 2] show significant performance for enhancement of ECG signals embedded with different types of noises. However, these techniques require prior information of the signal to work efficiently such as the position of the R peak for Empirical Mode Decomposition (EMD) based technique [1] and a reference signal for the Least Mean Square (LMS) algorithm based method [2]. This kind of information is difficult to obtain when the noise level is very high. The wavelet transform based techniques [3, 5] are more popular and widely used because of its ability to characterize time-frequency domain information of a time domain signal. However, the amplitude of the wavelet transform is dependent on the frequency. Wavelet Transform also has other limitations [10] such as having better frequency resolution and poor time resolution for low frequencies and vice versa for high frequencies. It also has locally referenced phase.

Here, a novel method for ECG signal enhancement is proposed using Stockwell Transform (S-Transform) to overcome the afore mentioned limitations. This method is a generalized approach that can be applied for different noises which often get embedded with ECG signal during its acquisition and transmission [1]. The proposed method does not require any prior information like R peak position or reference signal as auxiliary signal. The S-Transform, derived by Stockwell et al. [11], is closely related to the Wavelet Transform (WT) and Short Time Fourier Transform (STFT). The S-Transform (ST) has a similar form to the STFT except that the width of window varies with frequency [10]. The S-Transform have three characteristics that distinguishes it from Wavelet Transform: (i) Frequency invariant amplitude response (ii) Progressive resolution and (iii) Absolutely referenced phase information [11]. Besides, the ST uses time-frequency axis rather than the time-scale axis used in the WT [10]. Therefore the interpretation on the frequency information in the ST is more straight forward than in the WT which will be beneficial to remove noise components. ST is used to represent the noisy ECG in time-frequency domain. An automatic mask window and morphological filtering technique is applied to this time-frequency domain represented noisy signal for removing the noises. The proposed algorithm is evaluated for noises such as muscle artifact, electrode motion, baseline wander and white gaussian noise. Performance of the proposed algorithm is evaluated by means of Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE). Experimental results show that the proposed method yields superior performance compared to commonly used Wavelet Transform based technique [5].

3.2 Theoretical Background

The S Transform was introduced by Stockwell *et al.* [12] inorder to obtain the time frequency representation of a time domain signal. The S-transform is similar to STFT except that this width and height of the analyzing window are permitted to scale with changes in the frequency, which is similar to continuous wavelet transform. The continuous S-transform $S(\tau, f)$ is defined as [13]

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} \, e^{\frac{-(\tau - t)^2 f^2}{2}} \, e^{-i2\pi f t} \, dt \tag{3.1}$$

where *h(t)* is a input signal. A voice $S(\tau, f_o)$ is defined as a one dimensional function of time for a constant frequency f_o, which shows how the amplitude and phase for this exact frequency changes over time. If the time series *h(t)* is windowed (or multiplied point by point) with a window function (Gaussian function) *g(t)* then the resulting spectrum is

$$H(f) = \int_{-\infty}^{\infty} h(t)g(t)\, e^{-i2\pi ft}\, dt \tag{3.2}$$

where generalized Gaussian function is

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{t^2}{2\sigma^2}} \tag{3.3}$$

and then allowing the Gaussian to be a function of translation τ and dilation (or window width) σ.

$$S(\tau, f, \sigma) = \int_{-\infty}^{\infty} h(t)\frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{(t-\tau)^2}{2\sigma^2}}\, e^{-i2\pi ft}\, dt \tag{3.4}$$

This is a special case of the multiresolution fourier transform because there are three independent variables in it, it is also impractical as a tool for analysis. Simplification can be achieved by adding the constraint restricting the width of the window to σ to be proportional to the period (or inverse of the frequency).

$$\sigma(f) = \frac{1}{|f|}$$

The discrete S Transform [14] can be calculated by taking advantage of the efficiency of the fast Fourier transform (FFT) and the convolution theorem. Assume $h[kT]$, *k=0, 1,...,*$(N-1)$ denote a discrete time series corresponding to *h(t)* with a time sampling interval of T. The discrete Fourier transform is defined as

$$H\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} h\left[kT\right] e^{\frac{-j2\pi nk}{N}} \tag{3.5}$$

where *n=0, 1,...,*$(N-1)$. In the discrete case, the S-transform can be considered as the projection of the time series vector $h[kT]$ onto a set of vectors. These vectors are not orthogonal, and the elements of the S-transform are dependent on each

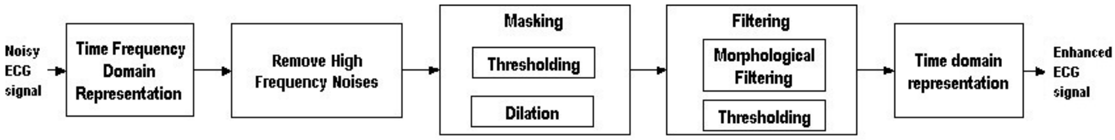

Figure 3.1: *Block Diagram of S-Transform based ECG enhancement technique*

other. The fourier transform basis vectors are divided into N localized vectors by multiplying with the N shifted Gaussian, such that by adding these N localized vectors we get the original basis vector. Assuming in equ. (3.5), $f \to n/NT$ and $\tau \to jT$) the S-transform of the discrete time series $h[kT]$ is giving by

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} h\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{-j2\pi j}{N}} \tag{3.6}$$

and for the $n = 0$ voice, it is equal to the constant which is defined as

$$S\left[jT, 0\right] = \frac{1}{N} \sum_{k=0}^{N-1} h\left[\frac{m}{NT}\right] \tag{3.7}$$

where j, m and n = *0, 1...*,$(N-1)$. The previous equation puts the constant average of the time series into the zero frequency voice [13] thus assuring the inverse is exact for the general time series. The discrete S-transform suffers the familiar problems from sampling and finite length, giving rise to implicit periodicity in the time and frequency domains. The calculation of the S-transform is very efficient, using the convolution theorem both ways, each to the advantage, and utilizing the efficiency of the Fast Fourier Transform (FFT) algorithm.

3.3 Methodology

The objective of the proposed algorithm is to achieve enhanced signal by selecting the required frequencies and removing the noise components. The block diagram of proposed S-Transform based ECG enhancement is shown in Fig. 3.1 and the different steps are explained below.

Step 1: Time-frequency domain representation: The S-Transform [12] is used to obtain the time-frequency representation of a time domain noisy ECG signal. The continuous S-transform $S(\tau, f)$ of a noisy ECG signal $h(t)$ at time

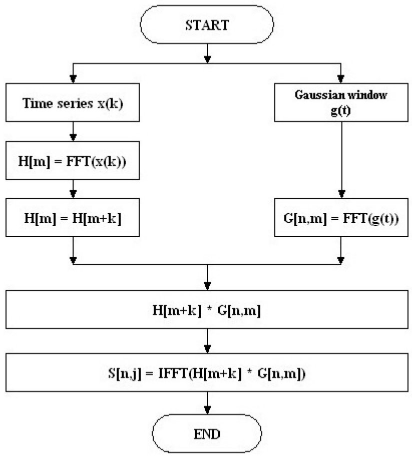

Figure 3.2: *Flowchart to calculate discrete S-Transform*

$t = \tau$ and frequency f is defined as

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} \, e^{\frac{-(\tau-t)^2 f^2}{2}} \, e^{-i2\pi f t} \, dt \tag{3.8}$$

The Discrete S-transform of the noisy ECG signal $h[kT]$ is given by

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} \, e^{\frac{i2\pi m j}{N}} \tag{3.9}$$

where $H\left[\frac{n}{NT}\right]$ is the Fourier Transform of $h\,[kT]$ and $j,\ m,\ n = 0,1,...,N-1$. Fig. 3.2 shows the computing procedure of Discrete S-Transform [10].

The time-frequency domain representation of a noisy ECG signal is shown in Fig. 3.3(a).

Step 2: Remove High Frequency noises: The objective of this step is to remove high frequency noise components by applying frequency domain thresholding. A clean ECG signal generally has a bandwidth of 0.05 to 100 Hz [15]. However, ECG signals of different beat types available in MIT-BIH arrhythmia database [16] has shown that it contain important information within 200Hz. Hence a frequency domain threshold has been defined at 200Hz such that the frequency components below 200Hz are retained and frequency components above 200Hz are removed. Fig. 3.3(b) shows the time-frequency domain representation S_1 after removing high frequency noises.

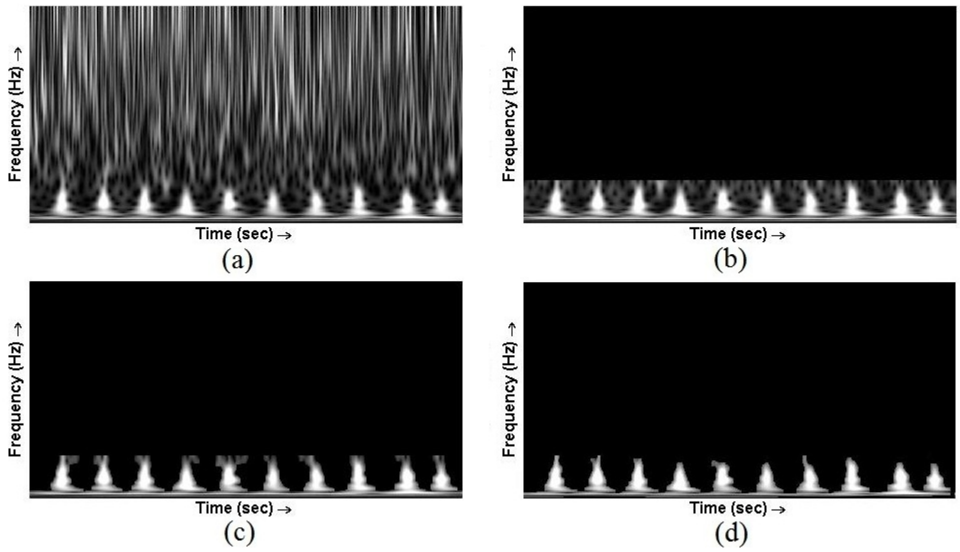

Figure 3.3: *Different stages of S-Transform based enhancement method: (a) Time-frequency domain representation of noisy ECG signal (b) Time-frequency domain representation of ECG signal after removing high frequency noise (c) Time-frequency domain representation of ECG signal after masking (d) Time-frequency domain representation of ECG signal after filtering*

Step 3: Masking: The objective of masking is to remove noise components whose frequencies are between the QRS complexes of time-frequency domain represented S_1. Firstly, the output of the previous step, S_1 is thresholded by selecting an appropriate threshold as T_m. The binary matrix B is obtained as follows

$$B[m,n] = \begin{cases} 1 & \text{if } S_1[m,n] > T_m, \\ 0 & \text{if } S_1[m,n] \leq T_m \end{cases} \tag{3.10}$$

where m and n represent row and column of S_1 and B. T_m is the threshold defined for m^{th} row of S_1. This threshold value T_m is selected such that the ratio of between-class variance σ_B^2 to the total-class variance σ_T^2 [17] is maximized. These two variables can be computed as follows.

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \tag{3.11}$$

$$\sigma_T^2 = \sum_{i=1}^{L}(i - \mu_T)^2 P_i \tag{3.12}$$

where

$$\omega_0 = \sum_{i=1}^{T_m} P_i \quad \text{and} \quad \omega_1 = \sum_{i=T_m+1}^{L} P_i$$

$$\mu_0 = \sum_{i=1}^{T_m} (iP_i)/\omega_0 \ \text{ and } \ \mu_1 = \sum_{i=T_m+1}^{L} (iP_i)/\omega_1$$

$$P_i = n_i/N \ (P_i \geq 0 \ ; \ \sum_{i=1}^{L} P_i = 1)$$

The output binary matrix B is dilated using a structuring element A_1 [18] as follows.

$$B \oplus A_1 = \{x | (\hat{A}_1)_x \cap B \neq \emptyset\} \tag{3.13}$$

where A_1 and B are considered as sets in 2-D integer space Z^2, $x = \{x_1, x_2\}$, $\hat{A}_1$ is the reflection of A_1 and $\emptyset$ is an empty set. Dilation expands the boundary of the white area in binary matrix and avoids any small breaks in the binary image. The largest connected area in this matrix is the second level mask M_1. The output of masking, $S_2 = S_1 \circ M_1$, is shown in Fig. 3.3(c).

Step 4: Filtering: Filtering's is used to smoothen the boundaries in time-frequency domain represented masked output S_2. This is done by performing following steps [18] on S_2.

1. Initially, S_2 is dilated using the smaller structuring element A_2 for more precise operation.

$$S_{21} = S_2 \oplus A_2 \tag{3.14}$$

   Here, dilation operation assigns each element the maximum value in the neighborhood defined by the structuring element A_2.

2. The dilated output S_{21} is eroded using A_2 using the following equation. Erosion is the opposite of dilation. Here, each element is assigned the minimum value in the neighborhood defined by the structuring elementA_2.

$$S_{22} = S_{21} \ominus A_2 = \{x | (A_2)_x \subseteq \emptyset\} \tag{3.15}$$

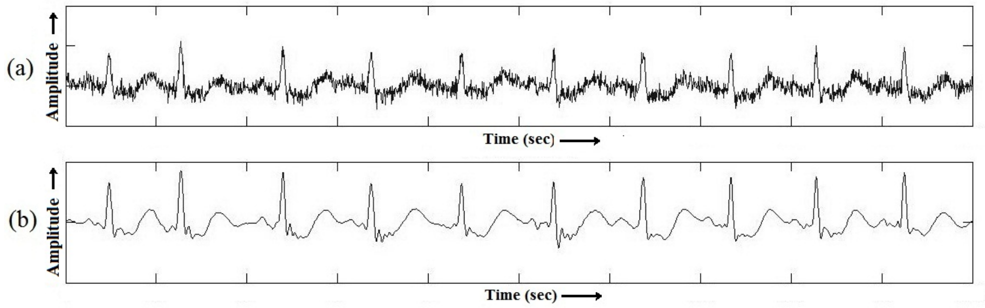

Figure 3.4: *S-Transform based enhancement: (a)Noisy ECG signal (Input) (b) De-noised ECG signal (Output)*

3. The eroded output S_{22} is opened by A_2. Opening is a combination of erosion and dilation. This step removes small unconnected areas and smoothen sharp peaks.

$$S_{23} = \{S_{22} \ominus A_2\} \oplus A_2 \tag{3.16}$$

4. The opened output S_{23} is closed by A_2. Closing is a combination of dilation and erosion. This step combines small breaks in the area and smoothen the boundaries.

$$S_{24} = \{S_{23} \oplus A_2\} \ominus A_2 \tag{3.17}$$

Finally the output matrix S_{24} is converted into a binary matrix using (3.10). Filtering is performed by multiplying S_2 with the resultant binary matrix M_2. The output of filtering, $S_3 = S_2 \circ M_2$, is shown in Fig. 3.3(d).

Step 5: Inverse S-Transform: The filtered time-frequency domain signal, S_3, is converted to time domain using the inverse S-Transform equation as

$$\hat{h}[kT] = \frac{1}{N} \sum_{n=0}^{N-1} \{ \sum_{j=0}^{N-1} S_3 \left[\frac{n}{NT}, jT \right] \} e^{\frac{j2\pi nk}{N}} \tag{3.18}$$

where $\hat{h}[kT]$ is the enhanced ECG signal. Fig. 3.4(a) shows the noisy ECG signal and Fig. 3.4(b) shows the enhanced ECG signal.

3.4 Results and Discussion

The proposed algorithm is tested on the ECG data available from online MIT-BIH arrhythmia database [16]. This database contains 48 different ECG signals with

30 minute duration which are sampled at 360Hz. Noise is added to these signals that result 0dB, 1.25dB and 5dB SNR. These noisy ECG signals are denoised using proposed method. The performance of the proposed method is compared with WT based technique [5] which is commonly used for ECG enhancement.

The performance of this method is evaluated based on the SNR and RMSE [19]. The SNR can be represented as follows

$$SNR = \frac{\sum\limits_{t=0}^{L-1} h(t)^2}{\sum\limits_{t=0}^{L-1} n(t)^2} \tag{3.19}$$

where $h(t)$ is the ECG signal and $n(t)$ is the noise signal. RMSE is used to evaluate the quality of the information which is preserved in the denoised ECG signal. RMSE is defined as follows:

$$RMSE = \sqrt{\frac{\sum\limits_{t=0}^{L-1} (h(t) - \hat{h}(t))^2}{L}} \tag{3.20}$$

where the numerator part is the square error, $\hat{h}(t)$ is the reconstructed ECG signal and L is the length of the ECG signal.

The proposed method is tested on different noises that are generally embedded with ECG signal during its transmission and acquisition i.e., gaussian noise, muscle artifacts, electrode motion and baseline wander.

3.4.1 Experimental Results with Gaussian Noise

Gaussian noise is used to model noise introduced due to poor channel conditions [1]. Gaussian noise is artificially added to ECG data from MIT-BIH database. Fig. 3.5(a) shows the Original ECG (MIT-BIH Record # 230) and Fig. 3.5(b) shows the ECG to which white gaussian noise is added resulting in an SNR of 1.25dB. Fig. 3.5(c) and Fig. 3.5(d) depict the denoised ECG signal using WT method and proposed method respectively.

Though both methods remove majority of the noise, it can be clearly seen from Fig. 3.5(c) that WT method output has more distortions. The amplitude of the Wavelet Transform is dependent on the frequency whereas S-Transform provides

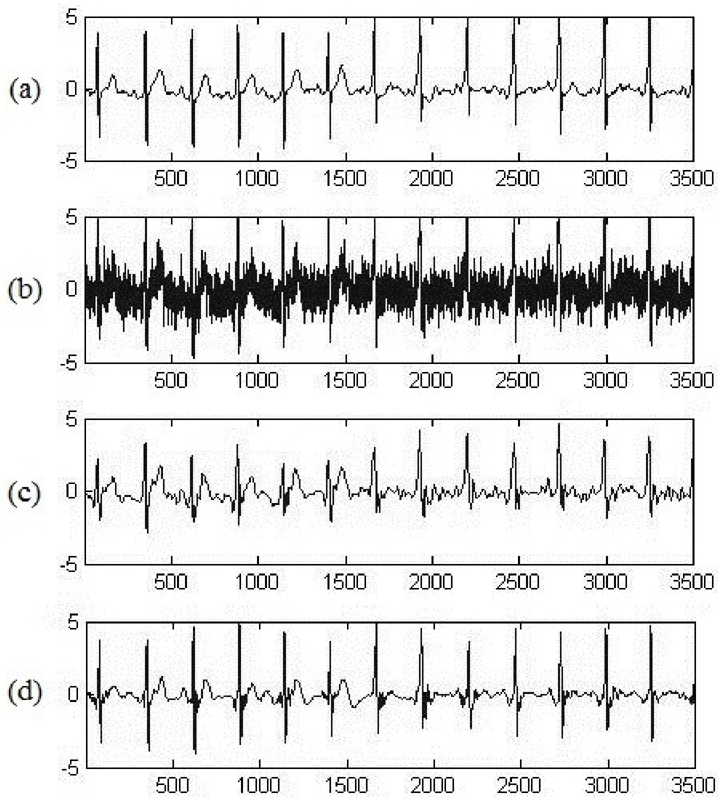

Figure 3.5: *Enhancement of ECG signal with Gaussian Noise: (a) Original Signal (MIT-BIH Tape No: 230) (b) Noisy Signal with 1.25dB SNR (c) WT method Output (d) Proposed Method Output*

uniform amplitude response for all frequncies [10]. This effect is evident in the WT method output which has lower R and S peak amplitudes.

Table 3.1 shows the comparison in SNR and RMSE for WT method and proposed method. The table contains comparative results for 10 different sets of data taken from MIT-BIH database. From the results, it is evident that the proposed method gives better performance with higher SNR and lower RMSE. For example, the results using Tape No: 122 shows that for an input SNR of 5dB, WT method gives an output with 9.77dB SNR. Meanwhile, the proposed method output has a higher SNR of 11.42dB. Similarly, the RMSE comparison shows that proposed method RMSE is 0.268 which is lower than the RMSE of WT method output i.e., 0.325.

Table 3.1: *Experimental Results for Gaussian Noise*

MIT/BIH	**0dB**				**1.25dB**				**5dB**			
	WT method		ST method		WT method		ST method		WT method		ST method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
103	5.84	0.511	9.96	0.318	6.72	0.461	10.95	0.284	9.66	0.330	12.91	0.226
105	7.35	0.429	8.85	0.361	7.96	0.400	9.95	0.318	10.22	0.308	13.54	0.210
111	7.04	0.445	7.55	0.419	7.72	0.412	8.38	0.381	9.62	0.330	10.09	0.313
116	6.63	0.466	7.95	0.401	7.37	0.428	8.73	0.366	9.65	0.329	9.82	0.323
122	6.69	0.463	8.32	0.384	7.47	0.423	9.32	0.342	9.77	0.325	11.42	0.268
205	5.45	0.534	8.45	0.378	6.31	0.484	9.15	0.349	8.57	0.373	10.10	0.313
213	5.92	0.506	8.14	0.392	6.62	0.467	9.42	0.338	8.74	0.366	12.49	0.237
219	7.25	0.434	8.94	0.357	8.02	0.397	10.03	0.315	10.36	0.303	12.54	0.236
223	7.35	0.429	9.56	0.332	8.10	0.394	10.81	0.288	10.87	0.286	13.86	0.203
230	5.73	0.517	9.93	0.319	6.44	0.476	11.05	0.280	8.85	0.361	13.14	0.220

3.4.2 Experimental Results with Real case noises

Real case noises such as Muscle Artifacts (MA), Electrode Motion (EM), and Baseline Wander (BW) are more probable during ECG acquisition [1]. These types of noises are more significant during stress test. For evaluating the proposed methodology, these noises are taken from the Noise stress database [20] and added to ECG data from MIT-BIH database.

Fig. 3.6 shows the experiment results for MA noise. Fig. 3.6(a) shows the Original ECG (MIT-BIH Tape No: 230) and Fig. 3.6(b) shows the ECG to which MA noise is added resulting in an SNR of 1.25dB. Fig. 3.6(c) and (d) shows WT method output and Proposed method output. Similarly Fig. 3.7(a) - 3.7(d) shows the experiment results for EM noise and Fig. 3.8(a) - 3.8(d) shows the experiment results for BW. The real case noises have frequency components in the same range as that of the Original ECG signal [21]. Output signals shown in Fig. 3.6 - 3.8 proves that WT method fails to remove these noise components and hence does not improve the signal quality. Meanwhile, the proposed method performs time-frequency domain filtering by using an appropriate mask and hence exhibits better enhancement of signal quality .

Table 3.2 shows the SNR and RMSE comparison for WT method and proposed method using MA noise. Table shows that WT method does provide only a minor improvement in SNR and RMSE. For example, experiment results for Tape No: 105 shows that for 5dB input SNR, WT method output has an SNR of 5.37 whereas

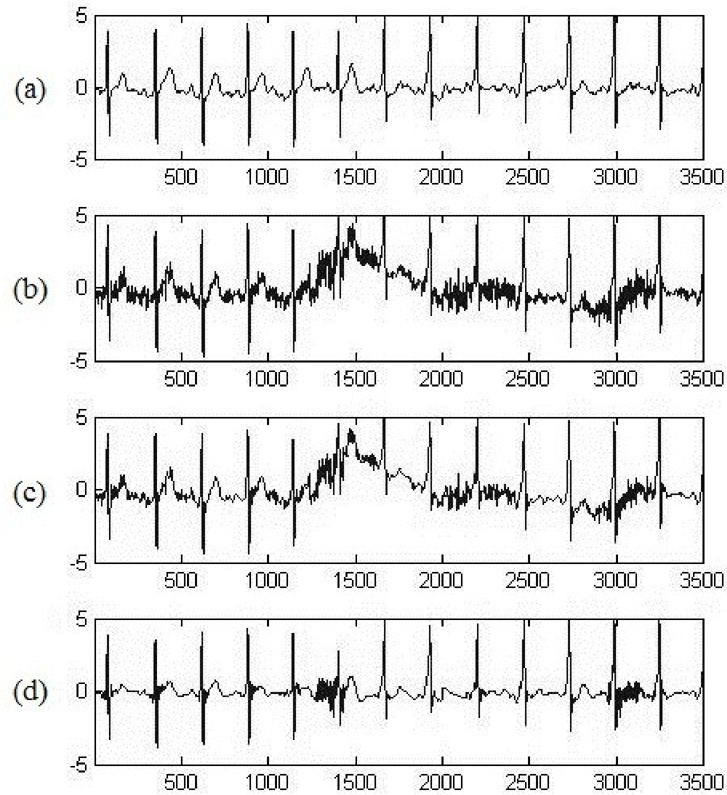

Figure 3.6: *Enhancement of ECG signal with Muscle Artifacts (MA) Noise: (a) Original Signal (MIT-BIH Tape No: 230) (b) Noisy Signal with 1.25dB SNR (c) WT method Output (d) Proposed Method Output*

the proposed method output has a higher SNR of 12.76. The RMSE of proposed method output is 0.230 which is very lower than RMSE of WT method output. The comparative results for other data also prove that the proposed method has superior performance with higher SNR and lower RMSE.

Table 3.3 shows the SNR and RMSE comparison for WT method and proposed method using EM noise. The comparative results show that WT method fails to improve the signal quality whereas the proposed method gives better performance. For example, the experiment results for Tape No: 230 with 5dB input SNR shows that there is no improvement in SNR for WT method output. Meanwhile, the proposed method gives an enhanced output with an SNR of 10.45dB. The proposed method output also has a RMSE of 0.3 which is lower than the RMSE of WT method output.

Table 3.4 shows the SNR and RMSE comparison for WT method and proposed method with baseline wander. The comparative results show that WT method

Table 3.2: *Experimental Results for Muscle Artifacts (MA) Noise*

	0dB				1.25dB				5dB			
MIT/BIH	WT method		ST method		WT method		ST method		WT method		ST method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
103	0.37	0.958	10.41	0.302	1.62	0.830	10.89	0.286	5.35	0.540	12.63	0.234
105	0.39	0.956	10.02	0.316	1.64	0.828	10.42	0.301	5.37	0.539	12.76	0.230
111	0.41	0.954	8.21	0.389	1.65	0.827	8.66	0.369	5.37	0.539	9.94	0.318
116	0.38	0.958	8.19	0.389	1.62	0.830	8.51	0.375	5.35	0.540	9.75	0.325
122	0.39	0.956	9.20	0.347	1.63	0.829	9.67	0.328	5.34	0.541	11.69	0.260
205	0.34	0.961	8.32	0.384	1.60	0.832	8.61	0.371	5.31	0.542	9.91	0.320
213	0.37	0.958	8.79	0.363	1.61	0.830	9.67	0.329	5.33	0.541	12.53	0.236
219	0.37	0.959	10.05	0.314	1.62	0.829	10.61	0.295	5.37	0.539	12.89	0.227
223	0.38	0.957	9.95	0.318	1.62	0.829	10.56	0.297	5.37	0.539	13.44	0.213
230	0.36	0.960	10.15	0.311	1.60	0.831	9.01	0.355	5.35	0.540	8.70	0.367

Table 3.3: *Experimental Results for Electrode Motion (EM) Noise*

	0dB				1.25dB				5dB			
MIT/BIH	WT method		ST method		WT method		ST method		WT method		ST method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
103	0.02	0.958	6.41	0.478	1.26	0.864	7.47	0.423	5.00	0.562	10.32	0.305
105	0.02	0.956	6.13	0.493	1.26	0.865	7.35	0.429	4.99	0.563	10.40	0.302
111	0.00	0.954	5.45	0.534	1.24	0.867	6.40	0.478	4.92	0.567	8.54	0.374
116	0.02	0.958	5.47	0.533	1.27	0.864	6.32	0.483	5.01	0.562	8.32	0.384
122	0.01	0.956	5.87	0.509	1.26	0.865	6.96	0.449	4.98	0.563	9.60	0.331
205	0.01	0.961	5.59	0.525	1.26	0.865	6.47	0.475	4.97	0.564	8.55	0.374
213	0.01	0.958	5.85	0.510	1.25	0.865	7.06	0.444	4.98	0.564	10.12	0.312
219	0.02	0.959	6.05	0.498	1.27	0.864	7.17	0.438	5.01	0.562	10.04	0.315
223	0.02	0.957	6.21	0.489	1.27	0.864	7.45	0.424	5.01	0.561	10.74	0.290
230	0.02	0.960	6.29	0.484	1.27	0.864	7.48	0.423	5.00	0.562	10.45	0.300

Table 3.4: *Experimental Results for Baseline Wander (BW) noise*

	0dB				1.25dB				5dB			
MIT/BIH	WT method		ST method		WT method		ST method		WT method		ST method	
Tape No	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
103	-0.01	1.001	11.40	0.269	1.24	0.867	12.06	0.249	4.97	0.564	13.54	0.210
105	-0.01	1.001	11.56	0.264	1.23	0.867	12.23	0.245	4.96	0.565	13.77	0.205
111	-0.04	1.004	9.22	0.346	1.20	0.871	9.61	0.331	4.89	0.569	10.41	0.302
116	-0.01	1.001	9.01	0.354	1.24	0.867	9.35	0.341	4.98	0.564	10.04	0.315
122	-0.01	1.002	10.58	0.296	1.23	0.868	11.17	0.276	4.95	0.565	12.38	0.240
205	-0.02	1.002	9.31	0.342	1.22	0.868	9.70	0.327	4.94	0.566	10.46	0.300
213	-0.01	1.001	11.57	0.264	1.23	0.867	12.22	0.245	4.96	0.565	13.77	0.205
219	0.00	1.000	11.55	0.265	1.24	0.866	12.22	0.245	4.99	0.563	13.65	0.208
223	0.00	1.000	12.14	0.247	1.25	0.866	12.95	0.225	4.98	0.563	14.81	0.182
230	-0.01	1.001	11.68	0.261	1.24	0.867	12.35	0.241	4.98	0.564	13.89	0.202

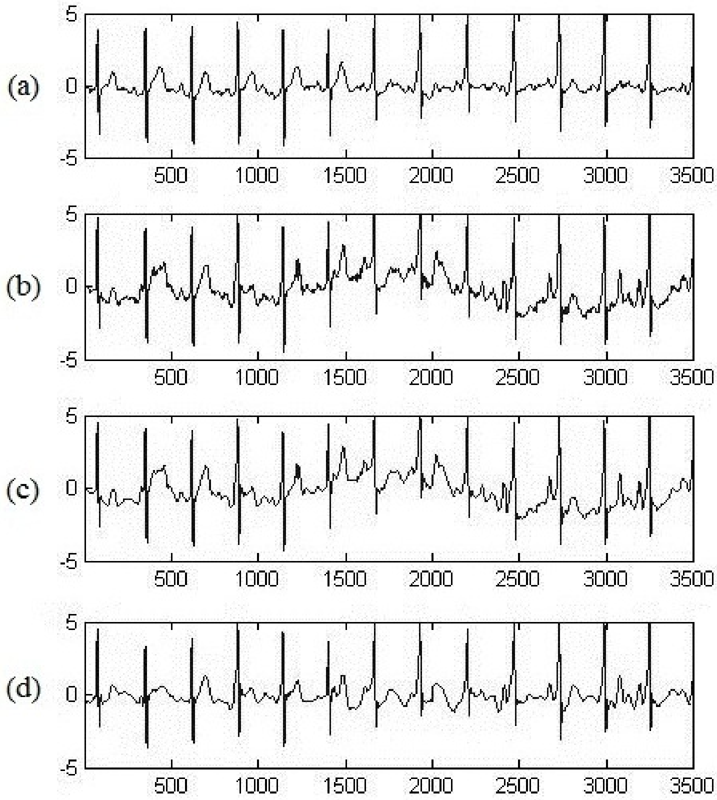

Figure 3.7: *Enhancement of ECG signal with Electrode Motion (EM) Noise: (a) Original Signal (MIT-BIH Tape No: 230) (b) Noisy Signal with 1.25dB SNR (c) WT method Output (d) Proposed Method Output*

fails as an enhancement technique for baseline wander. The WT method output has a slightly lesser SNR than the input SNR due to the distortions introduced during signal reconstruction. Meanwhile, the proposed method has a superior performance with higher SNR and lower RMSE. For example, the experiment results for Tape No: 122 with 5dB input SNR shows that WT method output has a degraded SNR of 4.95 whereas the proposed method gives a superior enhancement resulting in an output SNR of 12.38dB. The RMSE of proposed method output is 0.240 which is lower than the RMSE of WT method output.

3.5 Conclusion

Enhancement of ECG signals is required for accurate analysis of heart's condition. A generalized approach to ECG signal enhancement using S-Transform is proposed. The proposed method does not require any reference signal as auxiliary signal or prior information like R peak position. The noise components

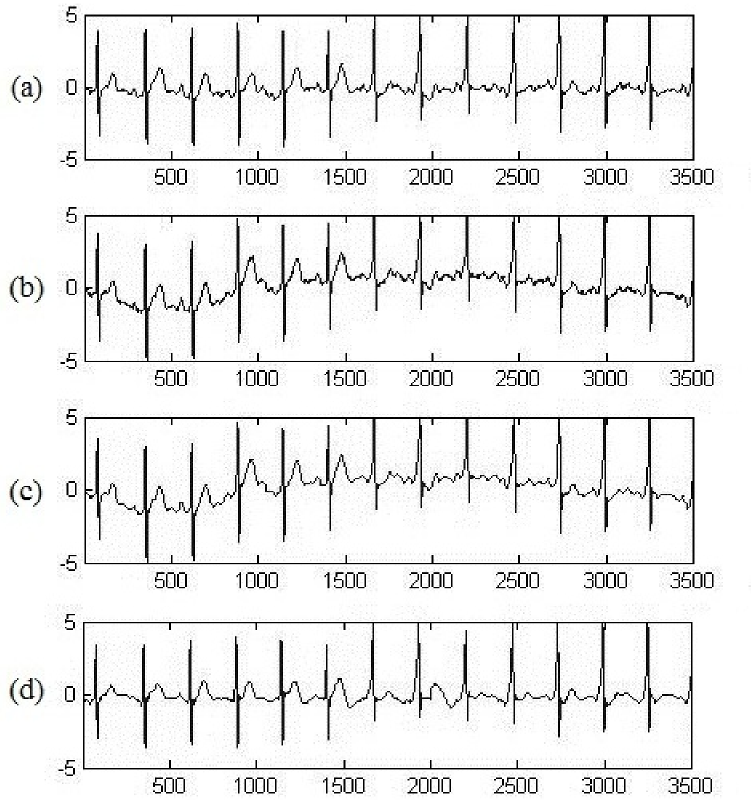

Figure 3.8: *Enhancement of ECG signal with Baseline Wander(BW): (a) Original Signal (MIT-BIH Tape No: 230) (b) Noisy Signal with 1.25dB SNR (c) WT method Output (d) Proposed Method Output*

are removed from the time-frequency domain represented noisy ECG signal by automatic binary masking and filtering. The proposed method is evaluated for different noises like White Gaussian Noise, Muscle Artifacts, Electrode Motion and Baseline Wander at three different SNR levels i.e., 0dB, 1.25dB and 5dB. Experimental results show that the proposed method performs with better SNR and lower RMSE compared to Wavelet Transform based technique which is usually used as an ECG signal enhancement technique.

3.6 References

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4
Concluding remarks

4.1 Conclusion

ECG enhancement is essential for automatic or manual ECG signal processing. This thesis explains two ECG signal enhancement techniques based on Empirical Mode Decomposition (EMD) and Stockwell Transform (S-Transform)

- Chapter 2 explains the ECG signal enhancement methodology using Empirical Mode Decomposition [1].The noisy ECG signal is decomposed into Intrinsic Mode Functions (IMFs) using EMD. Automatic detection of noisy IMFs is done using spectral flatness [2] measure. The noisy IMFs are filtered and then added with signal IMFs to obtain the denoised ECG signal. The proposed technique is evaluated on 5dB, 10dB and 15dB SNR where white gaussian noise is artificially added with original signal. Performance of the proposed method shows better SNR performance and lower RMSE for gaussian noise compared to Wavelet Transform based technique [3] which is usually used as an ECG signal denoising technique. However, the proposed methodology fails to perform as an enhancement technique for real case scenario.

- Chapter 3 explains the ECG signal enhancement methodology using S-Transform [4]. This method is a generalized approach to ECG signal enhancement using S-Transform. The proposed method does not require any reference signal as auxiliary signal or prior information like R peak position. The noise components are removed from the time-frequency domain represented noisy ECG signal by automatic binary masking and filtering. The proposed method is evaluated for different noises like White Gaussian Noise, Muscle Artifacts, Electrode Motion and Baseline Wander [5] at three different SNR levels i.e., 0dB, 1.25dB and 5dB. Experimental results show that the proposed method performs with better SNR and lower RMSE compared to Wavelet Transform based technique which is usually used as an ECG signal enhancement technique.

Both the techniques work as ECG enhancement techniques without using any prior information of the signal. However, EMD based technique cannot be used for multiple scenarios. It works well only with gaussian noise. On the other hand, S-Transform based approach can be applied for multiple noises and hence can be developed as a generalized approach.

4.2 Future work

The S-Transform based approach being the superior among the techniques discussed in this thesis, can be developed as a practical solution by performing the following steps

- Enhance the capability of the technique so that it can be also applied for the less common Powerline Interference.
- Clinical evaluation of the method by collecting data from ECG machines in normal and stress test conditions. Such an evaluation can be used to study the effectiveness of the method for unpredictable real life ECG acquisition scenarios.
- A hardware implementation of the technique can be done for interfacing it with ECG acquisition environment for real time applications. A software implementation with GUI can be developed if a off-line processing is planned.

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