Wavelet-Based Denoising of ECG Using Quantile-Based Dynamic Threshold Estimation

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by

Thota Tejasri
(11D070062)

under the supervision of

Prof. P. C. Pandey

Department of Electrical Engineering
Indian Institute of Technology Bombay
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M. Tech. Dissertation Approval

This dissertation entitled **"Wavelet-Based Denoising of ECG Using Quantile-Based Dynamic Threshold Estimation"** by **Thota Tejasri** (Roll No. **11D070062**) is approved, after the successful completion of *viva voce* examination, for the award of the degree of **Master of Technology** in **Communication and Signal Processing.**

Supervisor	……………………………… **(Prof. P. C. Pandey)**
Examiners	……………………………… **(Prof. V. K. Madan)**
	……………………………… **(Prof. V. Rajbabu)**
Chairperson	……………………………… **(Prof. V. Rajbabu)**

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(Thota Tejasri)

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ABSTRACT

Electrocardiogram (ECG) is a non-stationary biological signal which is useful in diagnosis of cardiac problems. It gets corrupted by several disturbances like electromyogram (EMG) noise, baseline wander, and motion artifact, particularly during ambulatory recordings. Removal of EMG noise is difficult due to significant spectral overlap between ECG and EMG noise. Wavelet-based thresholding has been reported to be effective for denoising ECG corrupted with EMG noise. It involves non-linear modification of wavelet coefficients at different levels after multilevel wavelet decomposition of the noisy ECG. For this purpose, use of quantile-based estimation of time-varying thresholds is investigated. It is evaluated by denoising the noisy signals with different SNR values, generated using ECG and EMG noise records from MIT-BIH database. SNR improvement and wavelet-weighted percentage root mean square difference (WWPRD) are used as performance indices. Errors in the clinically important features are also examined. Comparing the contributions of $D1$ removal and thresholding, with thresholds obtained by 90th percentile, it is seen that thresholding results in additional SNR improvement of 3.86 dB, 3.10 dB, and 1.54 dB for input SNR of -10 dB, -5 dB, and 0 dB, respectively. Visual inspections show that median followed by mean combination estimates the EMG noise envelope more effectively. High performance is shown by choosing 90-percentile in time-varying threshold for input SNR from -20 dB to 5 dB, while 75-percentile gives better results for input SNR from 5 dB to 15 dB. Results with 50-percentile are relatively low unless the input SNR itself is very high. The WWPRD values of 19.95, 22.07, and 22.92 for 90, 75, and 50 percentiles, respectively, for −10 dB input SNR also indicate the suitability of threshold estimation. The proposed denoising method also improves the estimation of clinically important features of P-wave amplitude, T-wave amplitude, and PR interval.

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CONTENTS

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List of abbreviations and symbols

Abbreviation/Symbol	Explaination
$D_i(n)$	unmodified wavelet coefficients at scale i
$\hat{D}_i(n)$	modified wavelet coefficients at scale i
DWT	discrete wavelet transform
$e(n)$	error signal
ECG	electrocardiogram
EM	motion artifact
EMD	empirical mode decomposition
EMG	electromyogram
ICA	independent component analysis
L	number of decomposition levels
MA	muscle artifact
MSE	mean square error
N_i	number of wavelet coefficients at level i
PRD	percentage root mean square difference
RMSE	root mean square error
$s(n)$	noise free ECG signal
S_i	transition span
SNR	signal-to-noise ratio
SURE	Stein's unbiased risk estimation
STFT	short-time Fourier transform
SWT	stationery wavelet transform
$T(i,n)$	discrete wavelet transform at scale i
TIWT	translation invariant wavelet transforms

w_i	weight for level i
WWPRD	weighted wavelet percentage root mean square difference
$x(n)$	noisy ECG signal
$y(n)$	denoised ECG signal
$\psi(t)$	mother wavelet function
ε	EMG denoisng control parameter
$p\varphi[\lvert D_i(n) \rvert]$	Φ percentile of wavelet coefficients at scale i
$\gamma(n)$	time-varying thresholding parameter
$\theta_i(n)$	limiting threshold at scale i

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Chapter 1

INTRODUCTION

1.1. Problem overview

Electrocardiogram (ECG) is a non-stationary biological signal associated with electrical activity of the heart and is measured using electrodes placed on specific locations of the body surface. Fig. 1.1 shows a typical ECG over a cardiac cycle with three characteristic segments P wave, QRS complex, and T wave associated with atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. The amplitudes, timing relationships, and shapes of these segments are useful in diagnosis of cardiac disorders. Ambulatory ECG are recorded while the patient is performing normal day-to-day activities like walking, stair climbing, sitting etc. These records are useful to detect certain disorders which may not get detected in recordings taken under rest or stress test. Ambulatory recordings are susceptible to noise and artifacts due to body movement and electrode movement, which make it difficult to get the diagnostic information.

The frequency spectrums of different components of ECG are spread over the range 0.05 – 150 Hz, with a 100 Hz bandwidth essential for diagnosis [2]. Ambulatory ECG is usually corrupted by artifacts like electromyogram (EMG), baseline wander, and motion artifact (MA). EMG is a bio-potential generated due to muscular activity. Baseline wander in the ECG signal is generally due to respiration or movement related to slow motion of electrodes. Electrode motion at the skin-electrode interface causes a change in half-cell potential and results in irregular baseline wander known as motion artifact. EMG, baseline wander, and motion artifact extend over 5 – 500 Hz, 0.01 – 1 Hz, and 1 – 10 Hz, respectively [2]. Fig. 1.2 indicates relative power spectra of ECG and its QRS complex, P and T waves, EMG noise, and motion artifact. Due to significant spectral overlap of artifacts and interfering noise with ECG, use of linear filters is not appropriate for suppression of interfering noise and motion artifacts.

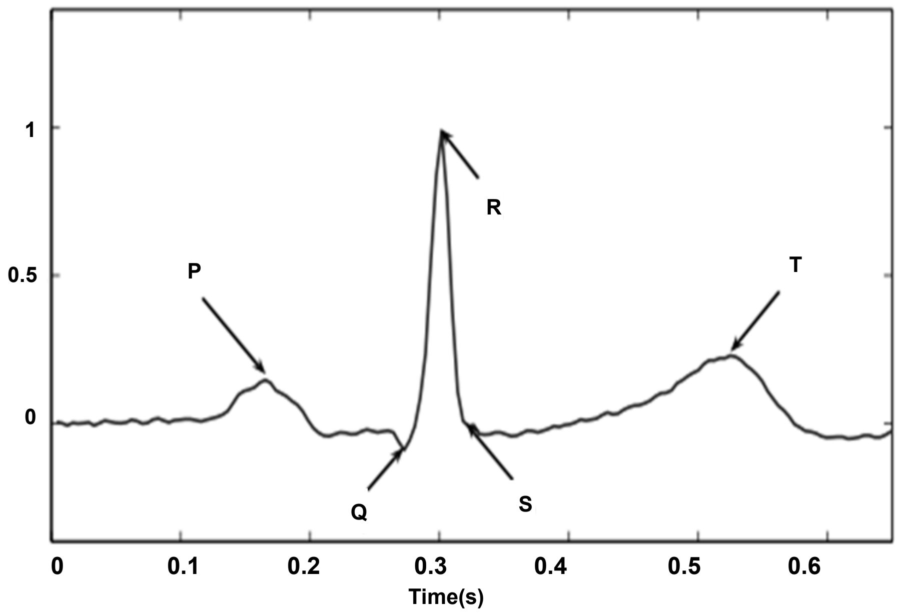

Figure 1.1 Typical ECG over a cardiac cycle [1].

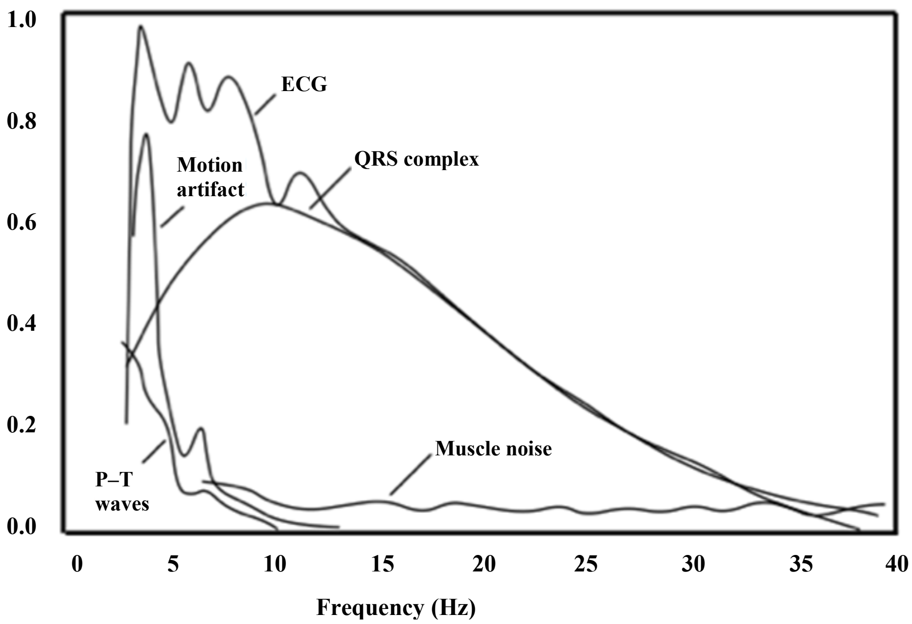

Figure 1.2 Relative power spectra of ECG and its QRS complex, P and T waves, muscle noise and motion artifacts based on average of 150 beats [2].

1.2. Objective

Several techniques for suppression of EMG noise in ambulatory recordings have been reported. The aim of the project is to investigate wavelet-based denoising of ECG signals for suppression of EMG noise. Level-dependent thresholding technique with quantile-based dynamic threshold estimation is investigated. Also the short-time estimate of EMG noise envelope from noisy ECG is investigated. The reported threshold estimation technique is validated on simulated noisy ECG signals using weighted wavelet percentage root mean square difference (WWPRD) and distortion in the clinically important features like P-wave amplitude, R-wave amplitude, T-wave amplitude, PR-interval, RR-interval, and QT-interval as qualitative evaluation measure. The technique is also validated using signal-to-noise (SNR) improvement as quantitative evaluation measure.

1.3. Outline of the dissertation

The ECG denoising techniques for suppression of noise and artifacts are reviewed in Chapter 2. The proposed wavelet-based denoising technique using quantile-based dynamic threshold estimation is presented in Chapter 3. Chapter 4 describes the method indices used for evaluation of the proposed technique and presents the test results. The last chapter provides summary and conclusion.

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Chapter 2

ECG DENOISING TECHNIQUES

2.1 Introduction

ECG recordings generally get corrupted by like EMG noise, baseline wander, and motion artifacts. Presence of these noise and artifacts cause errors in the detection of the clinically important features of the ECG signals. Due to spectral overlap between ECG and noise as shown in Fig.1.2, linear filters cannot be effective in denoisng. Several ECG denoising techniques have been reported based on digital and adaptive filtering, independent component analysis, empirical mode decomposition [3]–[6], and discrete wavelet transform (DWT) [7]–[15]. Some of these techniques are reviewed in this chapter.

2.2 Digital and adaptive filtering

Alste and Schilder [3] designed a digital filter with reduced number of filter coefficients for the removal of baseline wander and powerline interference. Effectiveness of the technique was verified by visual inspection. It was reported that the technique failed when the period of baseline wander cycle was close to the period of R-R interval. Rahman *et al.* [4] proposed normalized signed regressor least mean square (NSRLMS) based adaptive filter for baseline wander, power-line interference, EMG noise, and motion artifact cancellation. The proposed alogorithm was tested on noisy ECG recordings obtained by adding noise-free ECG recordings from MIT-BIH arrhythmia database with real noise from MIT-BIH Normal Sinus Rhythm Database (NSTDB) for validating suppression of different artifacts. SNR improvements of 7.80, 8.45, 8.50 dB were obtained for input SNR of 1.25 dB for baseline wander suppression, muscle artifact suppression, and motion artifact suppression, respectively.

2.3 Independent component analysis

Barros *et al.* [5] proposed use of independent component analysis for suppression of artifacts due to electrode movement, muscle movement, and respiration from noisy ECG. To estimate mixing parameters in real time, a self-adaptive step-size and two-layer neural network was used. Validation was carried out on simulated noisy ECG signals generated by mixing noise-free ECG with artifact taken from MIT-BIH noise stress test database. Visual inspection showed that two-layer ICA network performed better than digital filtering techniques. Foresta *et al.* [6] proposed an ECG denoising technique which combined the properties of wavelets with ICA. The technique was tested on multichannel ECG signals and a correlation coefficient of 0.9 was obtained between the artifact-free and denoised ECG.

2.4 Denoising using empirical mode decomposition

Velasco *et al*. [7] used empirical mode decomposition (EMD) to suppress baseline wander and EMG noise. The technique was validated on noisy ECG signals generated by adding artifact-free ECG from MIT-BIH arrhythmia database (records 100, 103, 105, 119, and 213) with signal-free artifact (records 'em' and 'ma') from MIT-BIH noise stress test. For input SNR of 6, 10, and 14 dB, the average output SNR of records were 10.24, 13.08, and 15.80 dB respectively.

2.5 Wavelet based denoising techniques

Zhang [8] proposed a technique for reducing the baseline wander and high-frequency noise using discrete wavelet transform (DWT). Two approaches were proposed for baseline wander correction. The first approach involved visual selection of approximation coefficients of a level matching the baseline wander among all approximation coefficients plotted for all possible levels. The second approach was to associate scaling and wavelet functions with half band low-pass and high-pass filters. The level of approximation coefficients where the frequency band has components below 1 Hz is approximated as baseline wander. Both the approaches were applied on simulated noisy ECG signal generated by adding ECG record 118 of MIT-BIH arrhythmia database with baseline wander record 'bw' from MIT-BIH noise stress test. Due to its similarity with QRS complex, sym10 was used as mother wavelet. It was reported that approximation A8 captures frequencies below 1 Hz, which is a good estimate of baseline wander. Suppression of high-frequency noise using wavelet shrinkage was based on sparsity property of wavelet transform. It removes noise effectively without affecting the sharp features of ECG signal. For suppressing high-frequency noise, translation-invariant wavelet transform (TIWT) with empirical Bayes posterior median threshold was used. Using sym8 as wavelet basis, 6-level wavelet decomposition, level-thresholding and TIWT were used for implementing the denoising technique. It has been reported that visual inspection of the processed waveform showed good results.

Kania *et al.* [9] studied the influence of mother wavelet selection and choice of decomposition level on denoising multi-lead high resolution ECG signals. Effectiveness of Daubechies (db2, db3, db4, db5, db6, db7, db8), Symlet wavelets (sym2, sym3, sym4, sym5, sym6, sym7, sym8), and biorthogonal wavelets (bior3.3, bio4.4, bio6.8) with different levels of decomposition was studied, with soft thresholding at each level and universal thresholds. The wavelets sym3 and sym8 for 4th decomposition level and the wavelet db1 for 4th and higher decomposition levels were found to preserve signal morphology.

Singh and Tiwari [10] reported that db8 was most appropriate wavelet function among Daubechies (order 4, 6, 8, 10, 12), Symmlet (order 4, 5, 6, 7, 8), Coiflet (order 1, 2, 3, 4, 5), and Battle–Lemarie (order 1, 3, 5) for denoising while preserving peaks of the ECG signal. It was reported that SURE shrink thresholding method with 'db8' as base wavelet had low root mean square error (RMSE).

Tikkanen [11] investigated wavelet based nonlinear denoising and wavelet packet based approach by applying soft and hard thresholding comparing the performance of four different thresholds: SURE, heuristic SURE, fixthresh, and minimax. Fifty simulated noisy ECG records with SNR 5 dB were created by adding Guassian, uniformly distributed white noise, and non-white noise to noise-free ECG. The results showed that wavelet denoisng approaches had better denoising performance than wavelet packet approaches in all cases except for heuristic SURE rule when using hard thresholding for white noises.

Sawant and Patil [12] analysed various threshold estimation techniques like universal, minimax, rigrsure/SURE shrink, and hybrid thresholds and reported that rigrsure has best SNR performance. ECG records 100, 102, 103 from MIT-BIH arrhythmia database was used for investigation. The techniques were evaluated by calculating SNR of denoised signal. Using Db5 wavelet and soft thresholding the average output SNR obtained were 6.9, 12.3, 11.8, and 13.1 dB for universal, minimax, hybrid, and rigrsure thresholds, respectively.

Poornachandra [13] proposed S-median threshold which is subband adaptive procedure for denoising white gaussian noise from the signal and its performance was compared with universal and minimax thresholds. Fifty signals from MIT-BIH arrhythmia database were used for investigation. For 0 dB input SNR, the output SNR of 20, 17, and 15 dB were obtained for S-median, minimax, and universal thresholds respectively indicating better performance of S-median threshold. It was observed that universal threshold tends to over smoothen the signal by killing significant coefficients which is not the case with S-median threshold due to its local adaptive nature and it has different threshold for each scale and thus results in less distortion and better denoising.

Mithun and Pandey [18] investigated wavelet based denoising using level-dependent thresholding for suppressing EMG noise in ECG signals. Threshold estimation was carried out based on level of noise in the signal for each scale. Test signals were taken from MIT-BIH database with SNR improvement and R-peak detection as performance indices. For input SNR of -10, -5, 0 dB, SNR improvements of 12.1, 8.8, and 5.1 dB, respectively were reported. False R-peak detection rate decreased from 14.5 % to 2.2 %. It was also reported that the values of L2 norm and maxmin based improvement indices were close to one indicating efficient denoising.

Pranava [15] carried out further investigations using the denoising technique reported in [14] and with discrete Meyer wavelet for EMG and motion artfifact suppression. Stationary wavelet transform (SWT) and TIWT were investigated to suppress pseudo-Gibbs oscillations introduced during denoising using DWT. The improvement was evaluated by using SNR improvement, percentage RMS difference, L2 norm and maxmin based improvement indices and R-peak detection efficiency as performance indices. Artifact-free ECG signals from MIT-BIH arrhythmia database and ECG-free artifacts from MIT-BIH noise stress test were used to generate noisy signals. For input SNR of −10 dB, SNR improvements of 14.5, 15.0, 14.7 dB were obtained for DWT, TIWT, and SWT, respectively. Denoising resulted in improvement of QRS detection efficiency from 94.4% to 99.3% and the false peak detection was reduced from 21.2% to 14.4%. The denoising techniques were also validated for ambulatory ECG signals where QRS detection efficiency improved from 63.2% to 90.6% and false R-peak detection percentage reduced from 0.1% to 0.05%.

Chapter 3

WAVELET-BASED ECG DENOISING FOR SUPPRESSOIN OF EMG NOISE

3.1 Introduction

The chapter presents a wavelet-based denoising technique for suppressing EMG noise in noisy ECG. It involves decomposition of noisy ECG into wavelet coefficients using discrete wavelet transform followed by nonlinear modification of wavelet coefficients using thresholding for suppression of noise. The nonlinear modification is carried out with respect to level-dependent thresholds which are usually calculated from input noisy signal itself using certain models of the signal and noise components in the input.

3.2 Discrete Wavelet Transform

The wavelet transform decomposes the signal using dilated and translated versions of the wavelet function. It provides high time resolution and low frequency resolution in case of high frequencies and high frequency resolution and low time resolution in case of low frequencies, whereas in STFT time resolution is uniform for all frequencies [16].

The wavelet transform of a signal $x(t)$ with respect to the mother wavelet function $\psi(t)$ is defined as

$$T(i,n) = \frac{1}{\sqrt{2^i}} \int_{-\infty}^{\infty} x(t)\, \psi^*\left(\frac{t - n\, 2^i}{2^i}\right) dt \tag{3.1}$$

The wavelet coefficients for discrete time input is denoted as $D_i(n)$ and detail for a given scale i denoted as D_i . For effective denoising, the mother wavelet should match the signal or the noise component at specific scales and locations. As the noise and artifacts in ECG do not have a specific shape, the mother wavelet function should match the shape of the ECG signal.

3.3 Thresholding

Thresholding is carried out for modifying the wavelet coefficients in order to reduce the noise. Wavelet coefficients $D_i(n)$ at scale i are modified to get $\hat{D}_i(n)$ using threshold θ. Modification using hard thresholding is carried out using

$$\hat{D}_i(n) = \begin{cases} 0, & |D_i(n)| \le \theta \\ D_i(n), & |D_i(n)| > \theta \end{cases} \tag{3.2}$$

An alternative approach is soft thresholding given by

$$\hat{D}_i(n) \;\; = \begin{cases} 0, & |D_i(n)| \le \theta \\ \operatorname{sgn}(D_i(n))(|D_i(n)| - \theta), & |D_i(n)| > \theta \end{cases} \tag{3.3}$$

Hard thresholding introduces discontinuities in the coefficient values and may lead to distortions in the form of ringing in the output. Soft thresholding may lead to attenuation of signal components. To avoid disadvantages of these thresholding functions, mixed or improved thresholding may be used as given below:

$$\hat{D}_i(n) \;\; = \begin{cases} 0, & |D_i(n)| \le \theta_a \\ \operatorname{sgn}(D_i(n)) f(|D_i(n)|), & \theta_\mathrm{a} < |D_i(\mathrm{n})| \le \theta_\mathrm{b} \\ D_i(n), & |D_i(\mathrm{n})| > \theta_b \end{cases} \tag{3.4}$$

where $f(|D_i(n)|)$ is smooth transition between thresholds θ_a and θ_b. Sebastian [17] investigated several transition functions and reported that improved thresholding gave better performance than hard and soft thresholding. There were no significant differences between the SNR improvements obtained using different smooth transition functions. The following improved thresholding function with smooth transition given in [17] for ECG denoising is used in the denoising method proposed in the next section.

$$\hat{D}_i(n) = \begin{cases} 0, & |D_i(n)| < \theta_i(n) \\ \operatorname{sgn}(D_i(n))(|D_i(n)| - f(n)), & \theta_i(n) \le |D_i(n)| < \left(\theta_i(n) + \dfrac{S_i}{2}\right) \\ \operatorname{sgn}(D_i(n))(|D_i(n)| - g(n)), & \left(\theta_i(n) + \dfrac{S_i}{2}\right) \le |D_i(n)| < (\theta_i(n) + S_i) \\ D_i(n), & (\theta_i(n) + S_i) \le |D_i(n)| \end{cases} \tag{3.5}$$

where
$$f(n) = \theta_i(n)[1 - 0.5(e^{ar} - 1)/(e^{a} - 1)], \tag{3.6}$$

$$r = (|D_i(n)| - \theta_i(n))/(S_i/2) \tag{3.7}$$

$$g(n) = \theta_i(n)[0.5 - 0.5(e^{-ar} - 1)/(e^{-a} - 1)], \tag{3.8}$$

$$r = (|D_i(n)| - \theta_i(n) - S_i/2)/(S_i/2) \tag{3.9}$$

The factor a controls the transition between hard thresholding and soft thresholding. Setting $a \approx 3$ and the transition span, S_i is given as

$$S_i = 0.75\,\mathrm{p95}[|D_i(n)|],\ |D_i(n)| > \theta_i(n) \tag{3.10}$$

and the time-varying threshold is given as

$$\theta_i(n) = \varepsilon\gamma(n)\,\mathrm{p90}[|D_i(n)|] \tag{3.11}$$

3.4 The denoising method

For ECG signals acquired with sampling frequency 360 Hz, 8-level wavelet decomposition is carried out using discrete Meyer wavelet to obtain detail coefficients $D1-D8$ and approximate coefficients $A8$. In noisy ECG corrupted with EMG noise, the wavelet coefficients of noise are of lower amplitude when compared to wavelet coefficinets of ECG which makes thresholding a better choice for removal of EMG noise. Suppression of EMG noise is carried out in two steps. First step is threshold estimation, followed by thresholding using improved thresholding function given in (3.5). Computation of appropriate thresholds is a critical problem in wavelet-based ECG denoising. Time-varying quantile-based dynamic threshold estimation has been proposed.

EMG noise is represented significantly in first four detail coefficients, $D1-D4$. It is further observed that $D1$ contains only noise components and $D2$ contains high frequency noise and negligible signal components. Hence $D1$ combined with upsampled $D2$ can be used for dynamically estimating the level of EMG noise. As $D1$ captures significant amount of noise, significant amount of denoising of noisy ECG signal can be done by removing only $D1$ during reconstruction of signal from wavelet coefficients. Investigation is carried out to quantify the SNR improvement due to thresholding on $D2-D4$ whose results are presented in next chapter.

Time-varying threshold θ_i for scale i is dynamically calculated from the wavelet coefficients as the following

$$\theta_i(n) = \varepsilon\gamma(n)\,\mathrm{p}\varphi[|D_i(n)|] \tag{3.12}$$

where ε is EMG denoising control parameter (may be set as 0.8), $\gamma(n)$ is dynamically estimated scaling factor and $\mathrm{p}\varphi[|D_i(n)|]$ represents φ - percentile. The thresholds calculated are resampled at each scale to match the number of samples.

3.4.1 Short-time estimate of EMG noise

The scaling factor $\gamma(n)$ in the time-varying threshold is calculated as the following:

$$\gamma(n) = \begin{cases} 0, & D_{avg}(n) < D_L \\ \dfrac{D_{avg}(n) - D_L}{D_H - D_L}, & D_L \le D_{avg}(n) \le D_H \\ 1, & D_{avg}(n) \ge D_H \end{cases} \tag{3.13}$$

where $D_{avg}(n)$ is short-time estimate of EMG noise, moving average of $D1$ combined with upsampled $D2$, D_L is 5th percentile of $D_{avg}(n)$ and D_H is half of 95-percentile of $D_{avg}(n)$.

The short-time estimate of EMG noise is calculated using symmetrically placed averaging window of different lengths on the combination of $D1$ and upsampled $D2$. Investigation is done on using mean, median and combinations of mean and median for averaging. A non-linear smoother using a combination of running median and linear smoother mean can have desired properties like retention of transitions and filtering out large errors. It is seen that median followed by mean combination estimates the EMG noise envelope more effectively because using median first removes the spikes and the mean used next smoothens the ripples. Investigation is also done on use of different window lengths. A high window length for mean results in residual noise. A low window length for mean introduces signal distortion as it captures the fluctuations of both noise and signal in $\gamma(n)$. So an intermediate window length is chosen. The results are given in next chapter.

3.4.2 Quantile-based dynamic threshold estimation

The time-varying threshold is estimated as $P\varphi[|D_i(n)|]$ which represents φ- percentile of φ_i. Investigation showed that choosing percentile based on noise level results in better denoising. If the noise affecting the ECG signal is high, then higher thresholds are set, by taking higher percentiles. Choosing high thresholds even when the noise is low results in distortion of signal. Hence, fixing the 90-percentile in time-varying threshold is not proper for all levels of noise. The following method is proposed for changing φ- percentile dynamically without apriori knowledge of noise level in the input noisy signal. As detail coefficients $D1$ captures only EMG noise components, based on the percent of energy present in $D1$ of total energy in all the detail coefficients $D1-D8$, the percentile in time-varying threshold can be estimated. Higher the energy present in $D1$, higher percentile is chosen. This method did not show any consistent results for different records of ECG.

Chapter 4

TESTS AND RESULTS

4.1 Introduction

The proposed technique of threshold estimation is evaluated by applying it on simulated noisy ECG signals with known levels of EMG noise. The performance of the denoising technique is evaluated using quantitative and qualitative evaluation measures like improvement in SNR due to denoising and change in WWPRD. Also distortion in ECG features like P-wave amplitude, R-wave amplitude, T-wave amplitude, PR-interval, RR-interval, and QT-interval, which are useful in clinical diagnosis are examined. The implementation of denoising method is carried out in MATALB. The details of ECG and artifact records used for evaluation of the technique are described in Section 4.2. Evaluation measures used are explained in Section 4.3. The results of investigations are presented in Section 4.4.

4.2 Records used for validation

The denoising technique was validated on 20 records of simulated noisy ECG signals generated by adding noise-free ECG with signal-free EMG noise. Ten artifact-free records from MIT-BIH arrhythmia database (records 100, 101, 103, 105, 106, 112, 116, 118, 119, and 123) were added with two muscle artifacts (record 'ma') from MIT-BIH noise stress test database. Sampling frequency used in these records is 360 Hz.

At given SNR simulated noisy EG signals $x(n)$ are generated by adding pure ECG $s(n)$ with EMG noise $e(n)$

$$x(n) = s(n) + \alpha\, e(n) \tag{4.1}$$

where $\mathrm{SNR}_{\mathrm{in}}$ is given as

$$\mathrm{SNR}_{\mathrm{in}} = 20\log\alpha \tag{4.2}$$

Combinations of two records of EMG noise added to 10 records of noise-free ECG resulted in 20 records of simulated noisy ECG signals. All noise-free ECG and EMG noise records are scaled to have same RMS value.

4.3 Evaluation measures

4.3.1 Visual inspection of feature distortion

The quality of ECG signals for clinical diagnosis is evaluated by visual inspection of ECG features like P-wave amplitude, R-wave amplitude, T-wave amplitude, PR-interval, RR-interval, and QT-interval. After processing of the noisy ECG signal in order to remove noise and artifacts, these are the features inspected in time domain by the doctor to find cardiac disorders. However, this method does not provide an objective assessment.

3.2 Signal-to-Noise Ratio (SNR)

Improvement in SNR is a common quantitative evaluation measure [4], [15], and [16]. Noise-free signal $s(i)$ is required for this measure. Input $\mathrm{SNR}_{\mathrm{in}}$ is the SNR of noisy input whereas output $\mathrm{SNR}_{\mathrm{out}}$ is the SNR of denoised output, given as

$$\mathrm{SNR}_{\mathrm{in}} = 10\log\left(\frac{\sum_{i=1}^{i=N}(s(i))^2}{\sum_{i=1}^{i=N}(x(i)-s(i))^2}\right) \tag{4.3}$$

$$\mathrm{SNR}_{\mathrm{out}} = 10\log\left(\frac{\sum_{i=1}^{i=N}(s(i))^2}{\sum_{i=1}^{i=N}(y(i)-s(i))^2}\right) \tag{4.4}$$

where $s(i)$ is the noise-free reference signal, $x(i)$ is the noisy input signal and $y(i)$ is the denoised signal. Improvement in SNR, $\mathrm{SNR}_{\mathrm{impr}}$ is $\mathrm{SNR}_{\mathrm{out}} - \mathrm{SNR}_{\mathrm{in}}$ and is given as,

$$\mathrm{SNR}_{\mathrm{impr}} = 10\log\left(\frac{\sum_{i=1}^{i=N}(y(i)-s(i))^2}{\sum_{i=1}^{i=N}(x(i)-s(i))^2}\right) \tag{4.5}$$

4.3.3 Wavelet-Weighted Percentage Root Mean Square Difference

Al-Fahoum [19] proposed WWPRD as objective diagnostic distortion measure. The WWPRD is defined as,

$$\mathrm{WWPRD} = \sum_{i=1}^{L} w_i \mathrm{WPRD}_i \tag{4.6}$$

where L corresponds to number of decomposition levels, w_i is the weight for level i. WPRD_i is the percentage root mean square difference of the wavelet coefficients in level i which is defined as

$$\mathrm{WPRD}_i = \sqrt{\frac{\sum_{n=1}^{N_i}(D_i(n) - \tilde{D}_i(n))^2}{\sum_{n=1}^{N_i}(D_i(n))^2}} \tag{4.7}$$

where $D_i(n)$ and $\tilde{D}_i(n)$ are the wavelet coefficients of original and processed ECG signals. The weight w_i for level i is calculated as

$$w_i = \frac{\sum_{n=1}^{N_i}|D_i(n)|}{\sum_{i=1}^{L}\sum_{n=1}^{N_i}|D_i(n)|} \tag{4.8}$$

Higher value of WWPRD is an indicator of higher diagnostic distortion.

4.3.3 Distortion in clinically important features

Distortion in clinical features like amplitudes of P-wave, R-wave, and T-wave, and timing intervals like PR-interval, RR-interval, and QT-interval, are measured. Time error and amplitude error of noisy ECG and denoised ECG are compared with clean ECG. Time error is the difference between the time instants of feature occurrences and amplitude error is the percentage of amplitude difference between clean ECG and noisy or denoised of clean ECG amplitude.

4.4 Test results

The denoising technique was validated on 20 records of simulated noisy ECG signals of input SNR of the range −20 dB to 20 dB. ECG records of sampling frequency 360 Hz were used, 8-level wavelet decomposition is carried out using discrete Meyer wavelet to obtain detail coefficients $D1-D8$ and approximate coefficients $A8$. An example of 8-level wavelet decomposition of clean ECG and noisy ECG is shown in Fig. 4.1 and 4.2 respectively. These figures show that EMG noise is present mostly in detail coefficients $D1-D4$ where $D1$ of noisy ECG contains only noise components and $D2-D4$ contains both noise and signal components. Hence denoising technique involves removal of $D1$ and thresholding in $D2-D4$.

The results of denoising for comparing the contributions of $D1$ removal and thresholding (using thresholds obtained by 90^{th} percentile) are summarized in Table 4.1. It is seen that thresholding results in additional SNR improvement of 3.86 dB, 3.10 dB, and 1.54 dB for input SNR of -10 dB, -5 dB, and 0 dB, respectively.

The estimation of EMG noise envelope $D_{avg}(n)$ is done by taking moving average on the combination of $D1$ with upsampled $D2$. Variation in moving average such as mean, median and combinations of mean and median as shown in Fig. 4.3 to get better noise envelope. It can be seen that median followed by mean combination estimates the EMG noise envelope more effectively because using median first removes the spikes and the mean used next smoothens the ripples.

Performance of Quantile-based thresholds is compared with SURE shrink and universal threshold. The mean and standard deviation of output SNR vs input SNR from -20 dB to 20 dB are presented in Table 4.2. High performance is shown by 90-percentile for input SNR from -20 dB to 5 dB, while 75-percentile gives better results for input SNR from 5 dB to 15 dB. Results with 50-percentile are relatively low unless the input SNR itself is very high. Signal distortion occurs if high thresholds are chosen in case of high input SNR. It is seen that the 90-percentile results in lower standard deviation as computed for wide range of SNR and hence it may be considered as optimal choice for EMG suppression.

Plots of output SNR vs input SNR, for denoising obtained by $D1$ removal and thresholding with thresholds selected using 90, 75, and 50 percentiles are shown in Fig. 4.4. For low input SNRs, denoising results in nearly constant SNR improvements. The SNR improvements decrease for input SNR exceeding 5 dB. For input SNRs below 5 dB, thresholds obtained using 90-percentile give better SNR improvement. A comparison of denoising with different threshold estimators is given in Fig. 4.5. It is seen that quantile-based thresholds give better output SNR for a wide range of input SNR.

The WWPRD values summarized in Table 4.3 indicate that use of 90-percentile for input SNRs below 5 dB results in lower distortion. Low WWPRD values for input SNRs above 5 dB indicates that distortion is less for high SNRs.

The clinical feature distortion due to addition of noise to clean ECG signal and denoised ECG signal are tabulated in Table 4.4 and Table 4.5. P-wave amplitude, T-wave amplitude, and PR interval are getting improved after denoising. Robust features like R-wave amplitude, QT interval, and RR interval are not much affected due to noise and hence they can be measured without denoising.

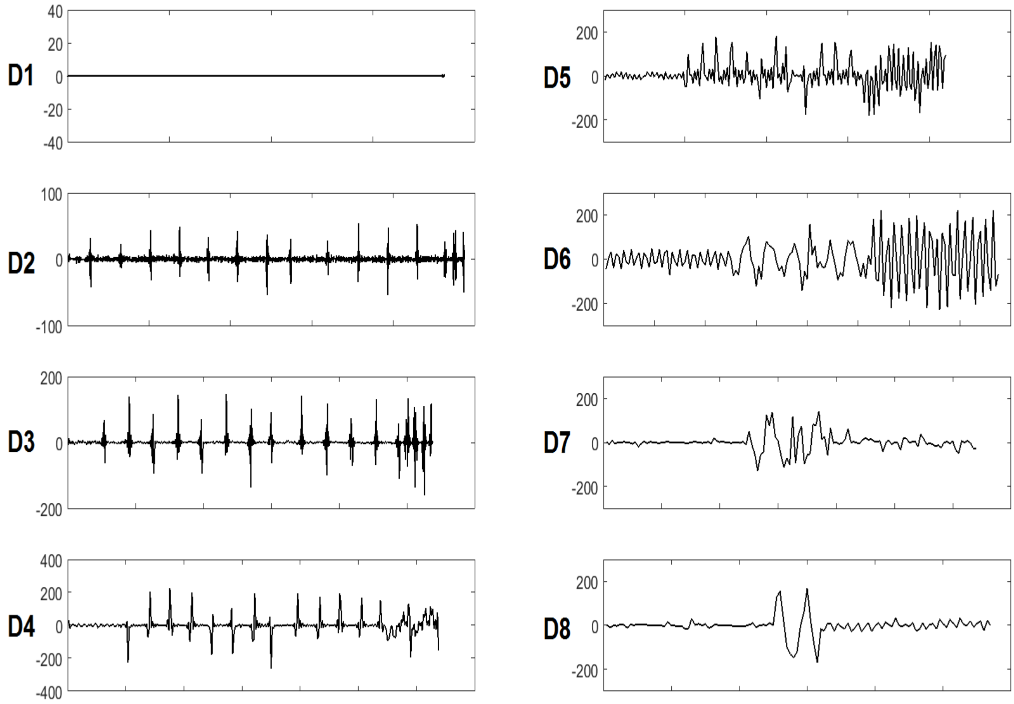

Figure 4.1 Example of decomposition of clean ECG signal (record 100).

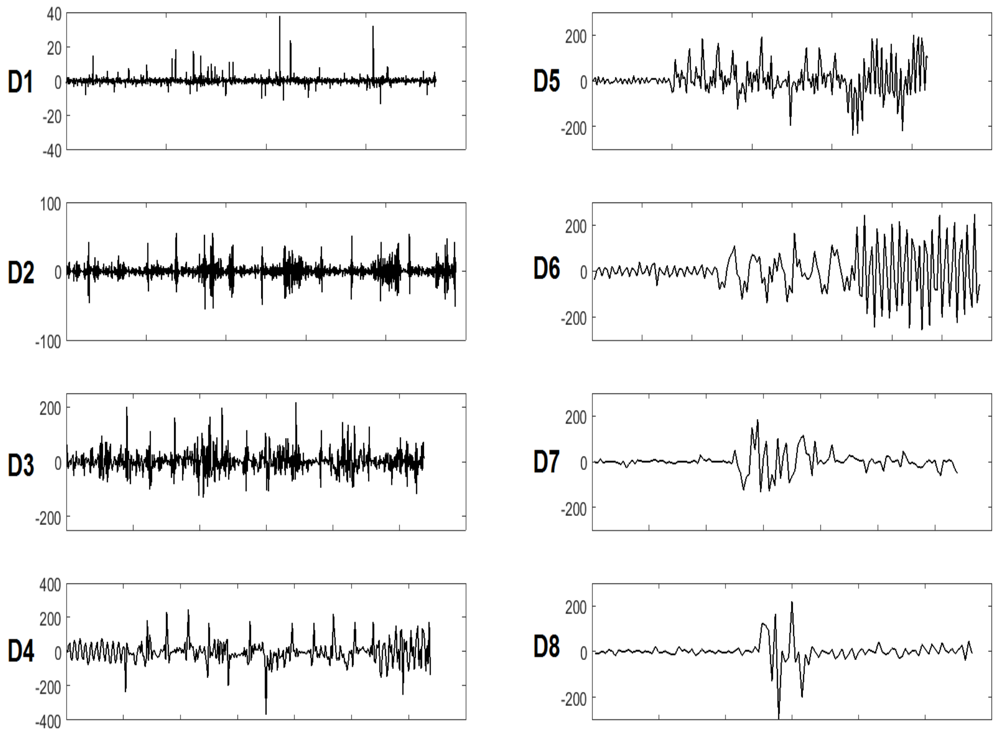

Fig. 4.2 Example of decomposition of noisy ECG signal (record 100 added to EMG noise, at SNR −5 dB).

Table 4.1. Output SNR vs input SNR for denoising using D1 removal and thresholding: Mean and Std. Dev. for 20 records.

Input SNR (dB)	Output SNR			
	D1 Removal		D1 removal & thresholding	
	Mean	Std	Mean	Std
−10	−4.41	0.61	−0.55	1.06
−5	0.59	0.61	3.68	0.82
0	5.57	0.6	7.11	0.56

Table 4.2. Output SNR vs input SNR for denoising and thresholds obtained by UT, SURE Shrink, and Quantile-based methods: Mean (Std. Dev.) for 20 records.

Input SNR (dB)	Output SNR (dB)									
	Universal threshold		SURE Shrink		Quantile-based threshold					
					P90		P75		P50	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
20	12.65	3.12	20.55	2.71	16.23	3.0	19.51	3.57	20.31	3.67
15	12.24	3.12	18.28	1.94	15.58	2.7	17.99	2.75	18.28	2.72
10	11.07	2.35	14.87	1.42	14.23	2.1	15.35	1.85	15.14	1.87
5	8.91	1.70	10.62	1.29	11.44	1.2	11.66	1.35	11.01	1.47
0	5.62	1.42	5.93	1.33	7.32	1.0	6.81	1.35	6.31	1.42
−5	1.45	1.49	1.04	1.36	2.43	1.1	1.77	1.41	1.37	1.44
−10	−3.21	1.64	−3.92	1.38	−2.68	1.2	−3.27	1.43	−3.62	1.45
−15	−8.06	1.77	−8.04	1.65	−7.71	1.27	−8.29	1.44	−8.62	1.46
−20	−13.00	1.83	−11.75	2.29	−12.68	1.28	−13.28	1.44	−13.62	1.46

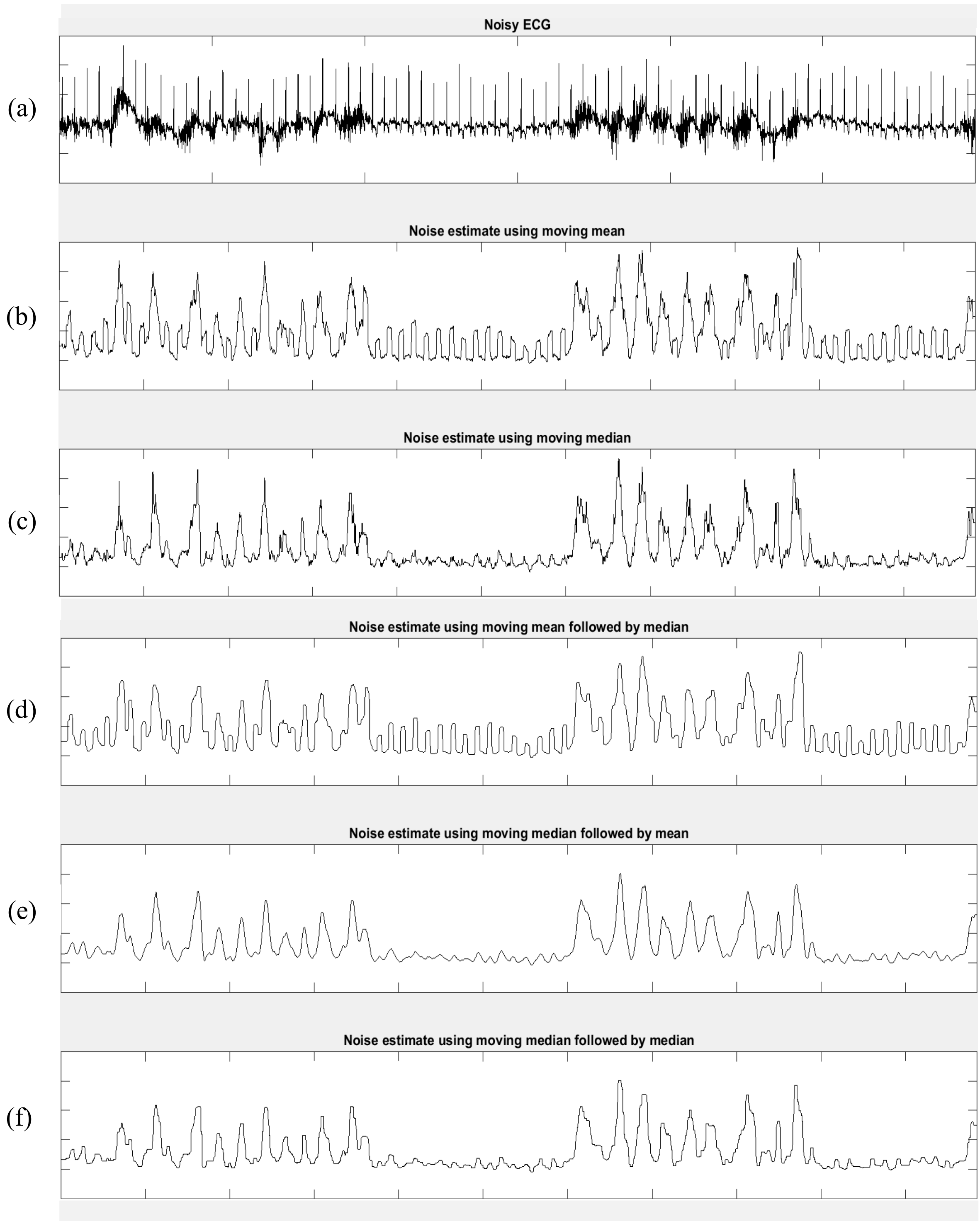

Fig. 4.3. (a) Noisy ECG. Noise estimate using (b) moving mean (c) moving median (d) moving mean followed by moving median (e) moving median followed by moving mean (f) moving median followed by moving median.

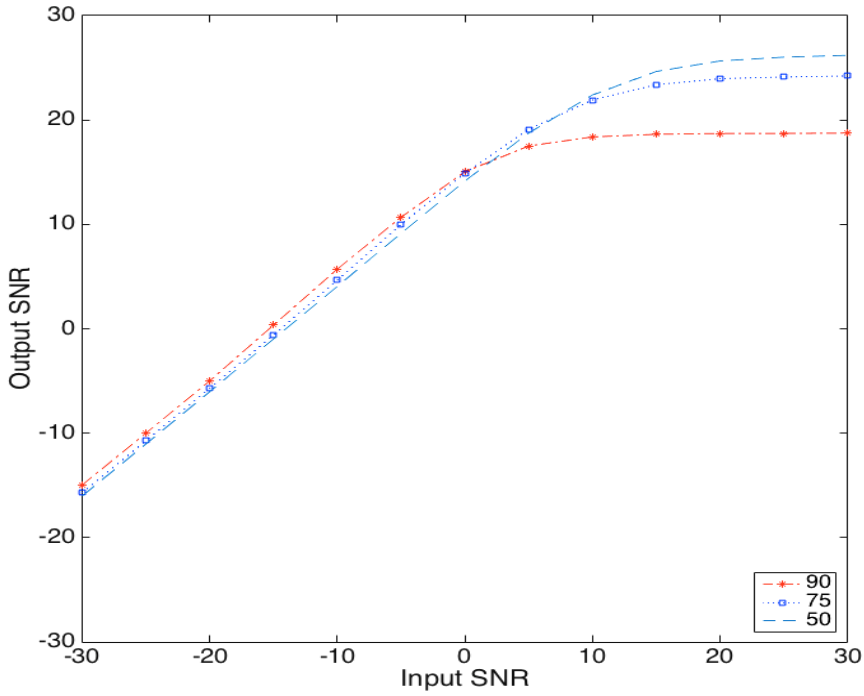

Fig. 4.4. Output SNR vs input SNR using quantile-based method for percentiles 90, 75, and 50.

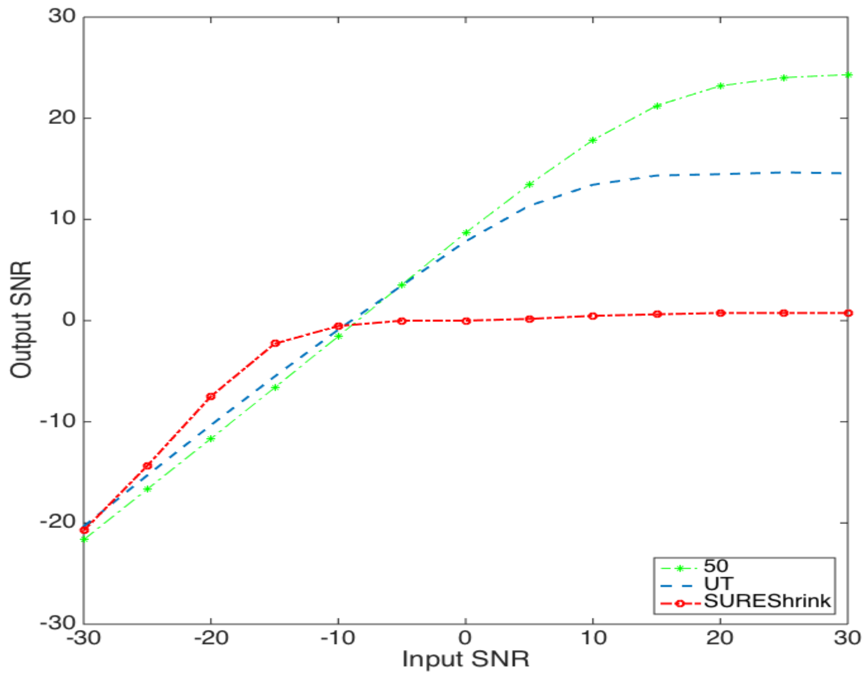

Fig. 4.5. A plot of output SNR vs input SNR for different threshold estimators.

Table 4.3. WWPRD values vs input SNR for denoising using Quantile-based thresholds with percentiles 90, 75, and 50: Mean and Std. Dev. for 20 records.

Input SNR (dB)	Quantile-based threshold					
	P90		P75		P50	
	Mean	Std	Mean	Std	Mean	Std
20	1.88	0.52	1.33	0.43	1.01	0.27
15	2.13	0.52	1.67	0.41	1.44	0.30
10	2.64	0.50	2.38	0.49	2.29	0.49
5	3.91	0.76	3.90	0.89	3.95	0.97
0	6.45	1.49	6.83	1.73	7.05	1.85
−5	11.34	2.76	12.26	3.19	12.69	3.38
−10	19.95	4.95	22.07	5.74	22.92	6.09
−15	36.06	8.91	39.79	10.29	41.38	10.89
−20	64.98	16.05	71.69	18.34	74.62	19.36

Table 4.4. Errors in P-wave amplitude, R-wave amplitude, and T-wave amplitude for record 100m at 0 dB input SNR and with time-varying threshold at percentile-90

Feature (Amp)	Clean ECG	Noisy ECG		Denoised ECG	
	Amp	Time error	Amp error	Time error	Amp error
P-wave	0.11	3.83	104%	−2.69	36.5%
R-wave	1.21	−0.14	1.6%	−0.11	9.7%
T-wave	0.04	6.00	32.2%	3.41	15.1%

Table 4.5. Errors in PR-interval, RR-interval, and QT-interval for record 100m at 0 dB input SNR and with time-varying threshold at percentile-90

Feature	Clean ECG		Noisy ECG		Denoised ECG	
	Mean	Std	Mean	Std	Mean	Std
PR interval	66.50	5.19	84.41	22.45	79.16	18.41
RR interval	294.81	9.45	294.72	9.65	294.79	9.78
QT interval	191.18	4.57	188.18	9.11	191.45	10.53

Chapter 5

SUMMARY AND CONCLUSION

Electrocardiogram is a non-stationary biological signal which consists of morphological features of P, T, and R wave amplitudes, width of QRS complex, time intervals between different points are used for diagnosis of cardiovascular disorders. These features get corrupted by various noises and artifacts like EMG noise, baseline wander, and motion artifact. Wavelet-based thresholding using dmey wavelet has been investigated for denoising of ECG corrupted with EMG noise. It involves non-linear modification of wavelet coefficients at different levels after multilevel wavelet decomposition of the noisy ECG. Quantile-based estimation of time-varying dynamic thresholds is investigated. It is evaluated by denoising the simulated noisy signals generated using ECG and EMG noise records from MIT-BIH database. SNR improvement, WWPRD, and distortions of clinically important features are used for evaluating the performance of denoising. Comparing the contributions of $D1$ removal and thresholding (using thresholds obtained by 90th percentile), it is seen that thresholding results in additional SNR improvement of 3.86 dB, 3.10 dB, and 1.54 dB for input SNR of -10 dB, -5 dB, and 0 dB, respectively. Visual inspections show that non-linear smoothening consisting of median followed by mean combination estimates the EMG noise envelope more effectively than other combinations of mean and median. Choosing 90-percentile in time-varying threshold for input SNR from -20 dB to 5 dB and 75-percentile for input SNR from 5 dB to 15 dB gave better SNR improvements. Results with 50-percentile are relatively low unless the input SNR itself is very high. The WWPRD values 19.95, 22.07, and 22.92 for 90, 75, and 50 percentiles respectively for −10 dB input SNR also indicated that use 90-percentile for low input SNRs resulted in lower feature distortion. Distortion in P-wave amplitude and T-wave amplitude got decreased from 104% to 36.5% and 32.2% to 15.1%, respectively.

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