Electromyography Noise Suppression in Electrocardiogram Signal Using Modified Garrote Threshold Shrinkage Function

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ABSTRACT
Electrocardiogram (ECG) waveform can be defined as graphical presentation of the heart activity over time. During ECG signal acquisition, some unwanted signals known as noise are mixed with the pure ECG signal. Electromyography (EMG) noise is a type of noise often encountered during ECG acquisition. EMG noise is particularly very difficult to suppress as it has very wide frequency spectrum between 6 Hz to as high as 10 kHz which overlaps with ECG frequency components. Accurate analysis and diagnosis of heart diseases becomes difficult due to these noise or artifacts. Therefore, there is need for noise suppression which is an inverse problem and is a signal recovery task. Several threshold shrinkage functions have been proposed for ECG signal de-noising in the wavelet transform domain. These include Hard Threshold Shrinkage Function (HTSF), Soft Threshold Shrinkage Function (STSF), Garrote Threshold Shrinkage Function (GTSF) and Hyperbola Threshold Shrinkage Function (HYTSF). In this work, a Modified Garrote Threshold Shrinkage Function (MGTSF) is developed for EMG noise suppression in ECG signal. The aim is to yield a better signal recovery with higher Signal to Noise Ratio (SNR) and Gain. In MGTSF, the universal threshold t is optimized by a tuning constant α. The performance of MGTSF is studied and is compared with existing threshold shrinkage functions with the aid of six ECG test signals. Optimum tuning constant is found to be 0.4. MGTSF is found to be effective for suppression of Electromyography (EMG) Noise in ECG signal. MGTSF yielded higher Signal to Noise Ratio (SNR) and Gain compared with HTSF, STSF, GTSF and HYTSF.

Keywords: *Electrocardiogram (ECG), Electromyography (EMG) Noise Suppression, Threshold Shrinkage Function, Wavelet Transform, Signal to Noise Ratio (SNR).*

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I. INTRODUCTION

Electrocardiography is a technique of recording the bio-electric current generated by the heart [1, 2]. It is a surface measurement of the electric potential generated by electrical activity in cardiac tissue which is caused by current flow in the form of ions. Electrocardiogram (ECG) waveform can be defined as graphical presentation of the heart activity over time [1, 2]. It is recorded by placing electrodes on the human body at certain points, and then measuring the potential difference between the electrodes caused by the depolarisations and repolarisations of the heart.

ECG waveform consists of six peaks and valleys namely P, Q, R, S, T and U as shown in Fig.1. Q, R and S are grouped together as QRS complex and it's the most important feature of an ECG signal. The ECG signal is divided into various segments as illustrated in Fig. 1. These segments represent different activities of the heart. For example, the P wave indicates atrial depolarization. The QRS complex and T waves indicate ventricular depolarization and ventricular repolarization respectively [3, 4, 5].

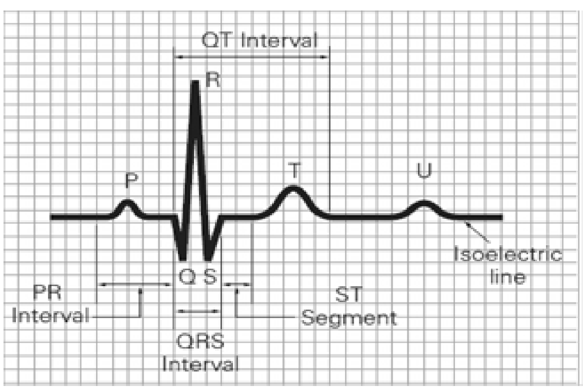

Fig. 1 ECG waveform [6].

Analysis of the electrical activities of the heart gives information about the health status of the heart. These electrical activities are displayed as waveform on Electrocardiogram (ECG) device monitor. ECG signal is acquired non-invasively through sensors. During ECG signal acquisition, some unwanted signals known as noise are inadvertently picked up as illustrated in Fig. 2 and as described in Eqn. (1). β is noise amplification factor which is a real number. β=30 is used in this work to simulate noticeable mix of the noise with the test signals. The point at which the noise is added in Fig. 2 is merely symbolic. Actually, the noise can enter the system at any point in the system.

$$X(n) = S(n) + \beta\eta(n) \quad (1)$$

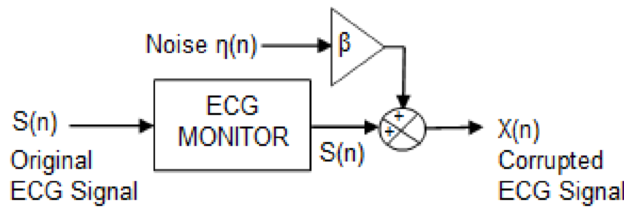

Fig. 2 Corruption of ECG Signal with noise.

There are many types of noise. These include artifacts due to muscle activities called electromyogram (EMG) and Power line interference caused by 50Hz/60Hz frequency of AC power supply inherent in our mains supply [4,7]. Baseline wander is another type of noise. Baseline wander is caused by placement of lead on bone, chest movement during respiration, restless movement, and improper grounding of patient's bed and equipment [8, 9]. Other types of noise are Channel noise and Electrode motion induced noise. EMG noise is particularly very difficult to suppress as it has very wide frequency spectrum between 6Hz to as high as 10 kHz which overlaps with ECG frequency components [10, 11]. The available ECG signal, X(n) of Eqn. (1) and Fig. 2 is not the same as the original ECG signal, S(n).

Accurate analysis and diagnosis of heart diseases becomes difficult due to these artifacts. Therefore, there is need for noise suppression. Noise suppression is an inverse problem; given X(n), deduce S(n). It's a signal recovery task.

Many efforts have been made in this direction and many noise-suppression techniques were developed among which are the adaptive filtering techniques such as Recursive Least Squares (RLS), Least Mean Square (LMS), and Normalized Least Mean Square (NLMS) [9, 12]. Data driven techniques such as Empirical Mode Decomposition (EMD) with Bayesian and Kalman filters for noise reduction were comparatively studied in [8]. EMD was found to be most suitable for ECG with high frequency noise [8].

Independent Component analysis (ICA) is a statistical approach proposed in [3] to suppress ECG noise. To preserve the characteristic ECG signal features, especially the QRS complex, the Wavelet transform technique has become very popular [10, 13]. Joy used Wavelet Transform and improved threshold function approach to reduce electromyography (EMG) artifacts from ECG signal [11]. Mithun et al. used Wavelet noise filtering technique with a combined effect of hard and soft thresholding functions to suppress EMG noise as well as motion artifacts in ECG signal [14]. This approach doesn't require prior knowledge of signal and noise characteristics like in adaptive filters.

Donoho and Johnstone developed the universal threshold value estimator [15]. Donoho proposed several wavelet shrinkage methods among which are Hard and Soft threshold functions which are very useful in the application of wavelet transform for noise suppression [16]. Ustundaug et al. discovered that interval dependent threshold performs better than hard and soft wavelet shrinkage techniques for very weak ECG signal [17].

In this paper, a Modified Garrote Threshold Shrinkage Function (MGTSF) is developed for EMG noise suppression in ECG signal. The aim is to yield a better signal recovery with higher Signal to Noise Ratio (SNR). The performance of MGTSF is studied and is compared with some conventional threshold shrinkage functions such as Hard Threshold Shrinkage Function (HTSF), Soft Threshold Shrinkage Function (STSF), Garrote Threshold Shrinkage Function (GTSF) and Hyperbola Threshold Shrinkage Function (HYTSF).

II. WAVELET TRANSFORM AND SHRINKAGE FUNCTION DENOISING SCHEME

Fig. 3 shows the wavelet transform and shrinkage function ECG de-noising scheme. The corrupted ECG signal X(n) which is a 1 by 2N sequence is the input to the scheme. L layers Discrete Wavelet Transform (DWT) [18-23] convert X(n) to Y(n) which is also a 1 by 2N sequence. Y(n) is partitioned into Detail Coefficients Yd(n) and Approximation coefficient Ya(n). Ya(n) is kept intact while Yd(n) is been modified by certain parameters and a shrinkage function to become Ydm(n). These parameters are deduced from Yd(n) itself. Ya(n) and Ydm(n) are recombined to yield Yp(n). Yp(n) is converted to Sr(n) by L stages Inverse Discrete Wavelet Transform (IDWT) [18-23]. Sr(n) is the recovered ECG signal which is expected to be very close to the true or original ECG signal S(n) of Fig. 2. Preservation of the important features of the signal such as the QRS complex is very crucial and is secured using this noise suppression scheme. This filtering scheme is adaptable for portable hard ware implementation as it's computationally not complex.

2.1 Wavelet Transform

A wavelet is defined as a small wave whose energy is concentrated in time. Wavelet is a tool for the analysis of transient, non-stationary or time-varying phenomena. There are various wavelet families such as Haar, Daubechies (Db), Sinc, Gaussian and Mexican Hat as shown in Fig. 4 [15]. Haar is used in this work. The signal X(n) is decomposed into two parts in each of L layers of wavelet decomposition as illustrated in Fig. 5. One is the approximate part (A) which contains the low-frequency information of the signal and the other is the details part (D) which contains the high-frequency information of the signal. A and D are obtained from the low pass (lp) and the high pass (hp) filters respectively. The relative dimensions of A and D after each layer of decomposition are indicated in Fig. 5. The formation of Ya(n) and Yd(n) from A's and D's for L = 1, L =2 and L =3 are also indicated in Fig. 5; Ya(n) and Yd(n) for L > 3 can be obtained in a similar manner. Total number of elements in both Ya(n) and Yd(n) is 2N. MATLAB code "wavedec" implements wavelet transformation to convert X(n) to Ya(n) and Yd(n) [24].

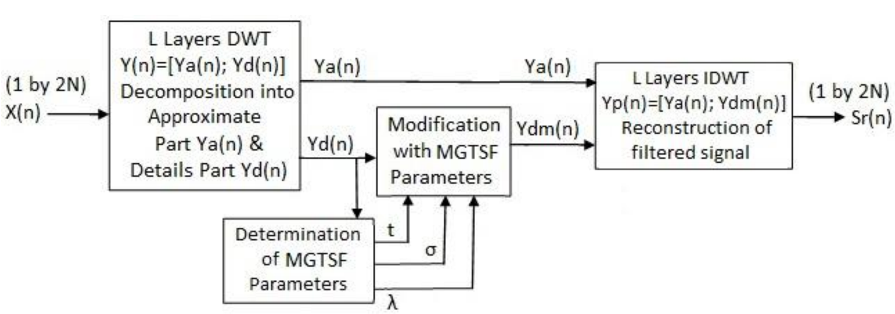

Fig. 3 Wavelet Transform and Shrinkage Function ECG De-noising Scheme.

Fig. 4 Some wavelet families.

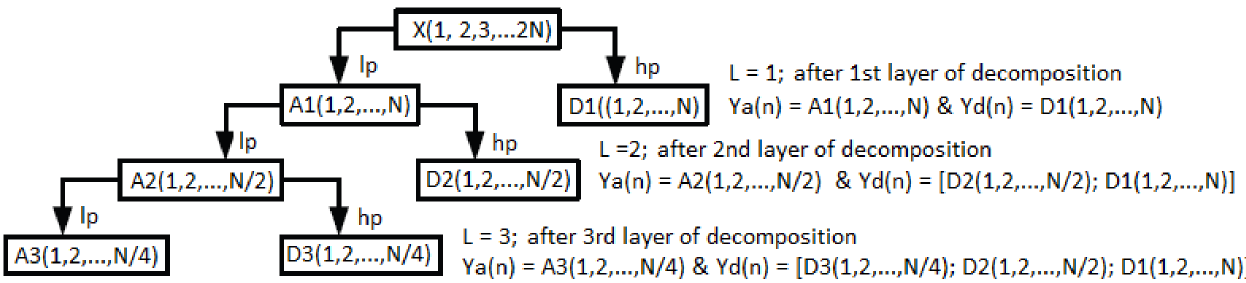

Fig. 5 Block diagram of three layers wavelet decomposition [25].

2.2 Wavelet Shrinkage Parameters

One of the most popular shrinkage policy proposed by Donoho and Johnstone is the Universal threshold while the standard functions are the Hard Threshold Shrinkage Function (HTSF) and Soft Threshold Shrinkage Function (STSF) [25, 26]. However, several other policies such as Stein's Unbiased Risk Estimator (SURE) and shrinkage threshold functions such as Hyperbola Threshold Shrinkage Function (HYTSF) and Garrote Threshold Shrinkage Function (GTSF) were later developed [26, 27]. The Universal threshold t is given as in Eqn. (2). A sequence $Yd^1(n)$ is generated from Y(d) as given by Eqn. (3). σ is defined as the noise level and is given by Eqn. (4) [15, 17, 26]. λ is proposed in this work as a modification of the universal threshold value which is given as in Eqn. (5). The universal threshold t [16, 17, 19, 28] is a widely accepted threshold limit and it is optimized in this work by a tuning constant, α.

$$t = \sigma\sqrt{2 \ln (N)} \quad (2)$$

where N is the length of the detail coefficients.

$$Yd^1(n) = \left|Yd(n) - median[Yd(n)]\right| \quad (3)$$

$$\sigma = \frac{median\ [Yd^1(n)]}{0.6745} \quad (4)$$

$$\lambda = \alpha t \quad (5)$$

where α is a tuning constant. α is in the range 0.2 to 1.0.

2.3 Threshold Shrinkage Function

A Shrinkage function is used to modify the details part Yd(n) to give Ydm(n). Existing shrinkage functions include HTSF, STSF, HYTSF and GTSF which are given by Eqns. (6), (7), (8) and (9) respectively [4,15,16,26,27]. In this work, a Modified Garrote Threshold Shrinkage Function (MGTSF) is introduced as given by Eqn. (10). Modified universal threshold (λ) and noise level (σ) are used in MGTSF. The wavelet transform and shrinkage function ECG de-noising scheme is coded into a software program in MATLAB working environment.

$$Ydm(n) = \begin{cases} Yd(n) & for\ |Yd(n)| > t \\ 0 & otherwise \end{cases} \quad (6)$$

$$Ydm(n) = \begin{cases} sgn[Yd(n)](|Yd(n)| - t) & for\ |Yd(n)| > t \\ 0 & otherwise \end{cases} \quad (7)$$

$$Ydm(n) = \begin{cases} sgn[Yd(n)]\sqrt{([Yd(n)]^2 - t^2)} & for\ |Yd(n)| > t \\ 0 & otherwise \end{cases} \quad (8)$$

$$Ydm(n) = \begin{cases} Yd(n) - \frac{t^2}{Yd(n)} & for\ |Yd(n)| > t \\ 0 & otherwise \end{cases} \quad (9)$$

$$Ydm(n) = \begin{cases} \frac{[Yd(n)]^2 - (\lambda - \sigma)^2}{Yd(n)} & for\ |Yd(n)| > \lambda \\ 0 & otherwise \end{cases} \quad (10)$$

2.4 Performance Metric

Filtering Scheme performance is evaluated using Signal to Noise Ratio (SNR) measured in dB. SNR_c of Eqn. (11) compares the acquired or corrupted ECG signal X(n) with the true or original ECG signal S(n). SNR_r of Eqn. (12) compares the filtered or recovered ECG signal Sr(n) with the true or original ECG signal S(n). The filtering Gain is given by Eqn. (13) [10, 11, 17, 29, 30, 31].

$$SNR_c = 10log_{10}\frac{\sum_{n=1}^{n=2N}[S(n)]^2}{\sum_{n=1}^{n=2N}[S(n)-X(n)]^2} \quad (11)$$

$$SNR_r = 10log_{10}\frac{\sum_{n=1}^{n=2N}[S(n)]^2}{\sum_{n=1}^{n=2N}[S(n)-Sr(n)]^2} \quad (12)$$

$$Gain = SNR_r - SNR_c \quad (13)$$

III. TESTS, RESULTS AND DISCUSSION

3.1 Electromyography (EMG) Noise and ECG Test Signals

The wavelet transform and shrinkage function ECG de-noising scheme is rigorously tested with six test ECG signals obtained from Massachusetts Institute of Technology-Beth Israel Hospital, MIT-BIH arrhythmia database [32, 33]. ECG signals with data record no 100, 101, 102, 103, 104, and 105 in the MIT-BIH arrhythmia data base were selected in this work as test ECG signals $S_1(n)$, $S_2(n)$ $S_3(n)$, $S_4(n)$, $S_5(n)$ and $S_6(n)$ respectively. Each of the test ECG signals has 1000 samples; 2N=1000. Each of the test ECG signals is normalized such that the actual signal amplitude A and normalized signal amplitude A_n are related by Eqns. (14) and (15). Each of these test ECG signals is corrupted with an electromyography (EMG) noise of Fig. 6 [32].

$$A = (A_n - 200)/2^{10} \quad (14)$$

$$A_n = 2^{10}A + 200 \quad (15)$$

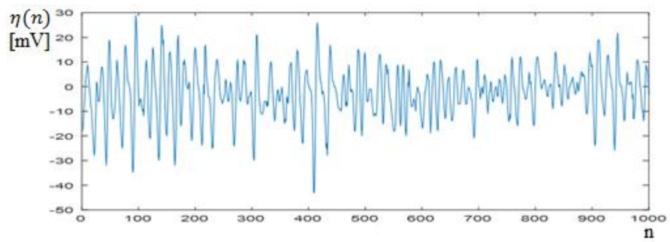

Fig. 6 Electromyography (EMG) Noise [32].

3.2 Determination of Optimal Tuning Constant

The six test ECG signals were corrupted with the EMG noise of Fig. 6. MGTSF scheme with varying values of the tuning constant (α) were used to filter the noisy signals. The Gain obtained with different Values of α for the six test ECG signals are presented in Table 1 and Fig. 7. A careful study of Table 1 and Fig. 7 give 0.4 as the optimum value of the tuning constant which gave the highest Gain for the six test signals.

Table.1: Variation of Gain with Tuning Constant for the Six Test ECG Signals.

Tunning Constant α	S_1 (n) Gain (dB)	S_2 (n) Gain (dB)	S_3 (n) Gain (dB)	S_4 (n) Gain (dB)	S_5 (n) Gain (dB)	S_6 (n) Gain (dB)
0.2	1.67	1.70	1.68	1.73	1.74	1.58
0.3	6.62	7.27	6.99	7.53	7.55	5.91
0.4	9.40	9.23	9.61	8.52	8.40	7.65
0.5	9.02	8.43	8.50	7.11	7.68	7.54
0.6	8.32	7.93	7.76	6.36	7.03	7.09
0.7	7.10	7.80	7.58	6.16	6.50	6.24
0.8	6.76	6.85	6.98	5.97	5.62	5.62
0.9	6.24	6.42	6.27	5.82	4.86	5.38
1.0	5.75	5.76	6.10	5.57	4.33	5.23

3.3 MGTSF Filtering Results at Optimum Tuning Constant

The results obtained with MGTSF filtering at optimum tuning constant (α = 0.4) for the six test signals are presented in Table 2. The waveforms of the original test ECG signal, corrupted ECG signal and the recovered ECG signal for two of the test ECG signals are shown in Fig. 8. MGTSF filtering

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is found satisfactory for suppression of electromyography (EMG) noise in ECG signal.

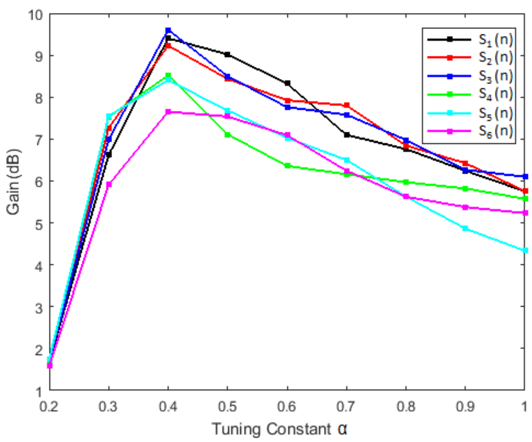
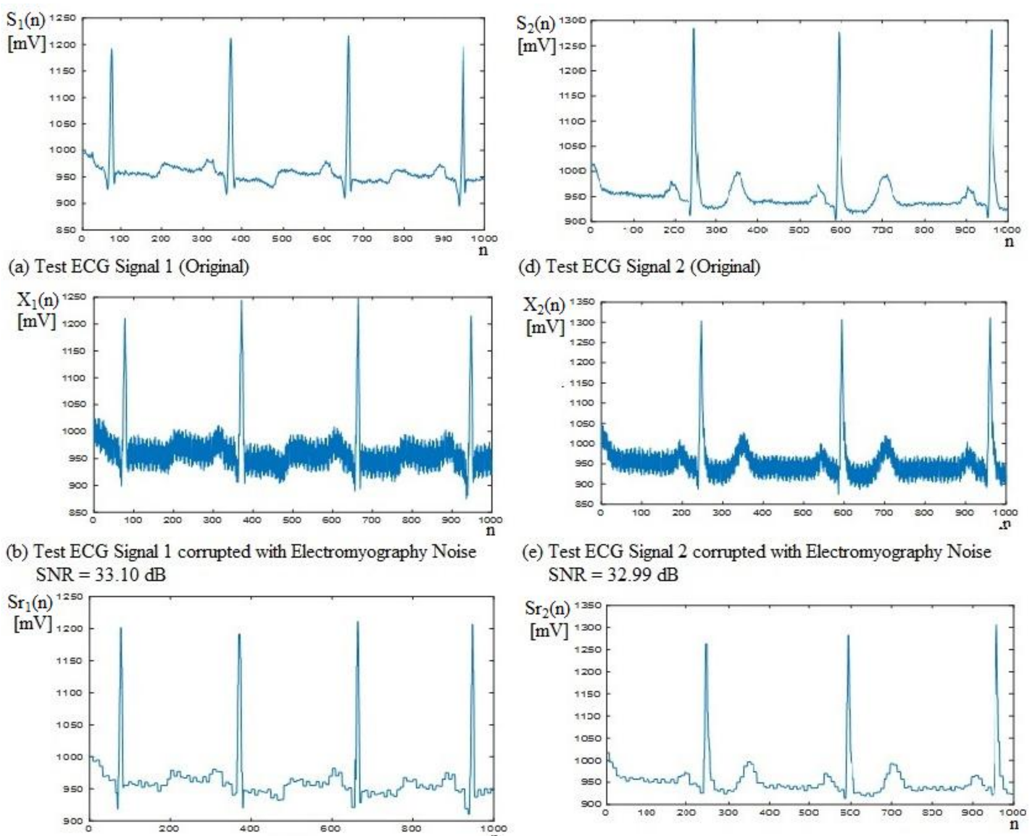


Fig. 7 Variation of Gain with Tuning Constant for the six ECG test signals.

Table 2: MGTSF Filtering Results at Optimum Tuning Constant ($\alpha = 0.4$) for the six Test ECG Signals

Test Signal	SNR_c (dB)	SNR_r (dB)	Gain (dB)
$S_1(n)$	33.10	42.50	9.40
$S_2(n)$	32.99	42.22	9.23
$S_3(n)$	33.30	42.91	9.61
$S_4(n)$	33.28	41.79	8.52
$S_5(n)$	33.24	41.64	8.40
$S_6(n)$	33.26	40.91	7.65



(a) Test ECG Signal 1 (Original)

(d) Test ECG Signal 2 (Original)

(b) Test ECG Signal 1 corrupted with Electromyography Noise SNR = 33.10 dB

(e) Test ECG Signal 2 corrupted with Electromyography Noise SNR = 32.99 dB

(c) Recovered Test ECG Signal 1 with MGTSF SNR = 42.50 dB; Gain = 9.40 dB

(f) Recovered Test ECG Signal 2 with MGTSF SNR =42.22 dB; Gain = 9.23 dB

Fig. 8 MGTSF Filtering Results: waveforms of original, corrupted and recovered signals for two of the test ECG signals.

3.4 Comparison of MGTSF with Existing Shrinkage Functions

The results of MGTSF filtering with Optimum tuning constant ($\alpha = 0.4$) and the corresponding results obtained with HTSF, STSF, HYTSF and GTSF are presented in Table 3 and Fig. 9. The waveforms of the original test ECG signal, corrupted ECG signal and the recovered ECG signal for one of the test ECG signals for all the shrinkage functions are displayed in Fig. 10. MGTSF is found to perform better than the existing shrinkage functions as it yielded highest Gain for all the test ECG signals.

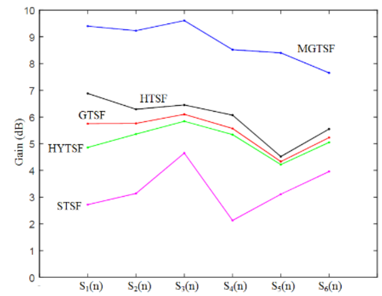


Fig. 9 Comparison of MGTSF, HTSF, GTSF, HYTSF and STSF Filtering Results for the six Test ECG Signals.

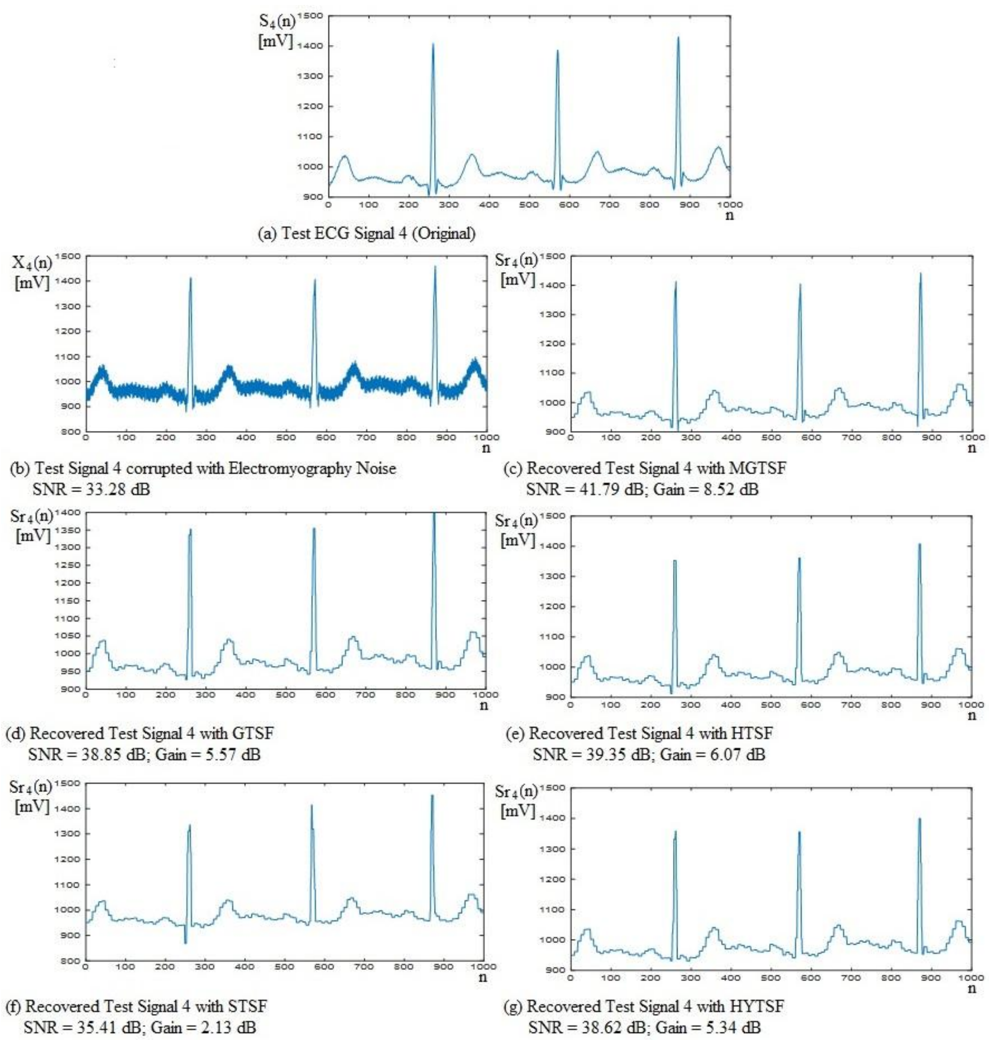


Fig. 10 Comparison of Shrinkage Functions: waveforms of original, corrupted and recovered signals for a test ECG signal.

Table 3: MGTSF, HTSF, GTSF, HYTSF and STSF Filtering Results for the six Test ECG Signals.

Gain (dB)					
Test Signals	MGTSF	HTSF	GTSF	HYTSF	STSF
$S_1(n)$	9.40	6.88	5.75	4.86	2.72
$S_2(n)$	9.23	6.29	5.76	5.36	3.14
$S_3(n)$	9.61	6.45	6.10	5.84	4.65
$S_4(n)$	8.52	6.07	5.57	5.34	2.13
$S_5(n)$	8.40	4.52	4.33	4.22	3.11
$S_6(n)$	7.65	5.55	5.23	5.05	3.96

All shrinkage functions shrink detail coefficients which are less than the universal threshold to zero. With tuning constant α =0.4, the actual threshold in MGTSF is less than the universal threshold. Therefore, MGTSF shrinks to zero less number of detail coefficients; it accommodates more detail coefficients. This accounts for MGTSF having the highest Gain.

All shrinkage functions shrink detail coefficients which are greater than the universal threshold towards zero except HTSF. The shrinkage in STSF is related to the noise level σ (t is proportional to σ) whereas the shrinkage in other functions are related to noise variance σ^2. Furthermore, the shrinkage in STSF has big bias due to the shrinkage of large coefficients which makes it much less sensitive to small changes in the data. These accounts for STSF having the least Gain.

IV. CONCLUSION

A Wavelet Transform based Modified Garrote Threshold Shrinkage Function (MGTSF) has been formulated for ECG signal de-noising which is essential for accurate analysis and diagnosis of heart diseases. Furthermore, the universal threshold has been optimized with tuning constant, $\alpha = 0.4$. MGTSF is found to be effective for suppression of Electromyography (EMG) Noise in ECG signal. MGTSF yielded higher Signal to Noise Ratio (SNR) and Gain compared with existing threshold shrinking functions.

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