Optimum Choice of Wavelet Function and Thresholding Rule for ECG Signal Denoising

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***Abstract*— This paper presents the optimal selection of thresholding rule and wavelet function for denoising an ECG signal. In the proposed work, a comparative study has been carried out using different wavelet functions and thresholding techniques. Thirteen wavelet functions ('db2', 'db3', 'db4', 'db5', 'db6', 'db8', 'sym4', 'sym6', 'sym8', 'coif2', 'coif3', 'coif4' and 'haar') and four thresholding rules ('Rigrsure', 'Heursure', 'Sqtwolog' and 'Minimaxi') are used. The efficacy of the denoising technique is demonstrated with the help of ECG datasets chosen from physiobank database. Three performance measures such as Signal to Noise ratio (SNR), Mean square error (MSE) and Peak signal to noise ratio (PSNR) are used for optimal selection of thresholding rules and wavelet functions in denoising ECG signal. The results of this study exhibits that the best performance of denoising ECG signal is obtained with the 'rigrsure' thresholding rule and 'coif2' wavelet function based on performance measures SNR, MSE and PSNR.**

Keywords*— Wavelet transforms, DWT, SNR, MSE, PSNR, and threshold

I. INTRODUCTION

World Health Organization (WHO) shows a statistics of 17.3 million deaths which have occurred worldwide due to the cardiovascular disease (CVD) [1]. One of CVD risk factors is atherosclerosis which can be predicted by myocardial ischemia detection. Myocardial ischemia is a cardiovascular disorder which affects the heart and the blood vessels. The coronary arteries become constricted by atherosclerosis which restricts the flow of blood and oxygen to the heart and results in heart attack or heart stroke. Myocardial ischemia is reflected in morphological variations in ECG as ST-segment deviation and T wave amplitude changes [2]. ECG signal represents the cardiac muscle activities. It is often gets contaminated with various types of noises such as baseline wandering, electromyogram noise, motion artifact, power line interference and contact noise.

Literature highlights the usage of different filters to remove the noise from ECG signals. This includes Weiner filtering and Kalman filtering methods for removing additive noises from ECG [3]. Authors of [3] demonstrated the loss of important clinical information from ECG signal using these techniques. To overcome this drawback, wavelet threshold based denoising technique is proposed [4] and is applied to noise removal from ECG signal. A novel wavelet based thresholding technique was used for noise removal where the threshold was computed using the minimum and maximum wavelet coefficients at each level [6]. For removing the noise from the weak ECG signals, an interval dependent thresholding method was proposed [7], where correlation coefficients and MSE are used as measures for evaluation of performance. Wavelet based thresholding methods are classified into soft and hard thresholding. After a thorough investigation, many researchers concluded that the soft thresholding is much better than the hard thresholding [5]. This work proposes soft thresholding with wavelet function for denoising of ECG signals. In this work, a comparative study has been carried out for proper selection of wavelet function and thresholding rule.

The organization of this paper is as follows. Section 2 presents the methodology adopted, ECG signal decomposition using wavelet transforms and thresholding rules. Next, performance indices adopted for evaluation of performance and experimental results for removal of noise from ECG signals are highlighted in section 3. Finally, conclusions are drawn at the end.

II. METHODOLOGY

Fig.1 shows the block diagram representation of the steps carried out in this work for comparison of various thresholding rules and different wavelet functions applied to ECG signals.

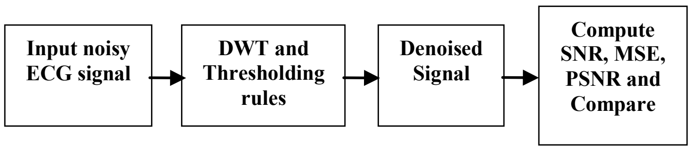

Fig.1. ECG signal denoising procedure

The ECG data is acquired from European ST-T datasets of physioBank database [8] contaminated with various noises which needs preprocessing before the feature extraction stage. In this work, 15 ECG signal samples of duration 1 minute each and at sampling frequency 250 Hz is randomly chosen for comparison. After the selection of ECG signals, fourth level DWT is applied with four soft thresholding rules. These rules

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include ‘Rigrsure’, ‘Heursure’, ‘sqtwolog’ and ‘Minimaxi’. Different wavelet functions applied in this work for comparison are daubeches, coiflet, symlet and haar. The performance measures used in this work are SNR, MSE and PSNR of denoised signal.

A. Wavelet Transform

Wavelet transform is a multiresolution analysis which decomposes the ECG beat into elementary wave components which are localized both in time and frequency. Discrete Wavelet Transform is computed by passing ECG signal sequentially through a high pass and a low pass filter [9]. This results in decomposition of the signal into approximation coefficients and detail coefficients. Fig. (2) shows the decomposition of ECG signal into low frequency and high frequency components up to 4 levels.

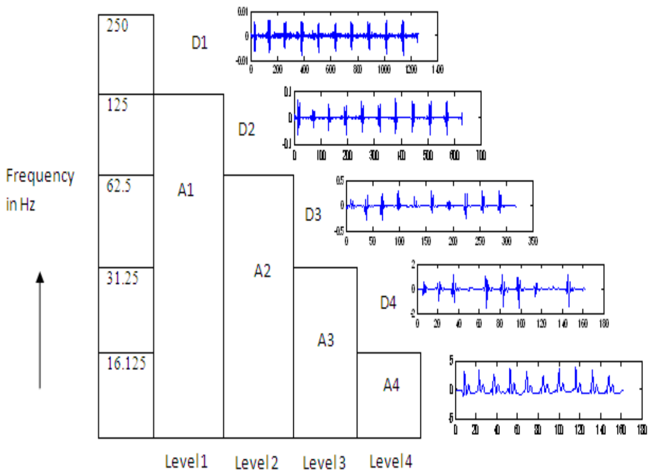

Fig.2. Structure of Wavelet Decomposition

The choice of the wavelet function depends on the type of signal to be analysed. In the present work, Daubechies, coiflet, symlet and haar wavelet functions are used, since those wavelet functions resemble the morphology of the ECG signal. Due to their symmetry with a QRS complex as well as concentration of energy spectrum at lower frequencies, these wavelets are utilized. The number of decomposition levels is chosen based on the dominant frequency components of the signal. In the present study, the numbers of decomposition levels are chosen to be 4 since most of the energy of the ECG signal lies between 0.5Hz and 40Hz [10].

B. ECG signal denoising based on wavelet thresholding

In this work, four different soft thresholding rules [11] are applied with DWT for its performance comparisons i.e. global, minimax, rigrsure and heursure thresholding rules.

- Global Thresholding: It is a type of fixed thresholding method and the threshold is calculated as

$$t = \sigma\sqrt{2\log(n)}$$

Where n is the total number of wavelet coefficients.

- Minimax Thresholding: It is the minimax performance for mean square error (MSE). It is a form of fixed threshold. It suitably selects the threshold value so as to minimize the error between the original signal and wavelet coefficients of noise signal.
- Rigrsure Thresholding: It is an adaptive thesholding method proposed by Donoho and Jonstone and is based on Stein’s unbiased risk estimation principle (SURE) [12]. Here, for each threshold value, find out its corresponding value at risk, and then choose a threshold to make the risk threshold value to be smallest.
- Heursure Thresholding: It is a combination of sure and global thresholding method. For poor SNR of signals, sure estimation fails. In such a situation, the fixed form of threshold is computed by means of global thresholding method [13].

C. ECG signal denoising based on wavelet thresholding

The performance of proposed denoising technique is evaluated by computing the signal to noise ratio (SNR), mean square error (MSE) and peak signal to noise ratio (PSNR), where

$$\mathbf{SNR\ in\ db} = \mathbf{10log_{10}}\left(\frac{\sum_{n=0}^{N-1}\{Xs(n)\}^2}{\{Xs(n)-Xr(n)\}^2}\right) \quad (1)$$

$$\mathbf{MSE} = \frac{1}{N}\left[\sum_{n=0}^{N-1}\{Xs(n) - Xr(n)\}^2\right] \quad (2)$$

$$\mathbf{PSNR} = \mathbf{10log_{10}}\left[\frac{255^2}{MSE}\right] \quad (3)$$

Where $X_s(n)$ is the original signal and $X_r(n)$ is the denoised signal.

III. Results And Discussions

Fig.3 shows the plot of SNR & MSE computed over ECG records e0103 and e0147 using the four thresholding rules ‘rigrsure’, ‘heursure’, ‘minimax’ & ‘universal’. From the plot it is observed that the best results are obtained consistently through ‘rigrsure’ thresholding rule for all three ECG records which are randomly chosen. Hence, it is concluded that the ‘rigrsure’ soft thresholding rule can be selected as best thresholding rule for denoising ECG signals.

Table 1, 2, 3 respectively shows SNR, MSE and PSNR values obtained due to the application of ‘rigrsure’ thresholding rule for 13 different wavelet functions over randomly selected 15 ECG datasets from physionet database. Bold letters indicates the best value between 13 wavelet functions of 15-ECG datasets. From the table 1, 2, 3 it is inferential that the “coif2” wavelet function gives the best SNR, MSE and PSNR while comparing with other wavelet functions.

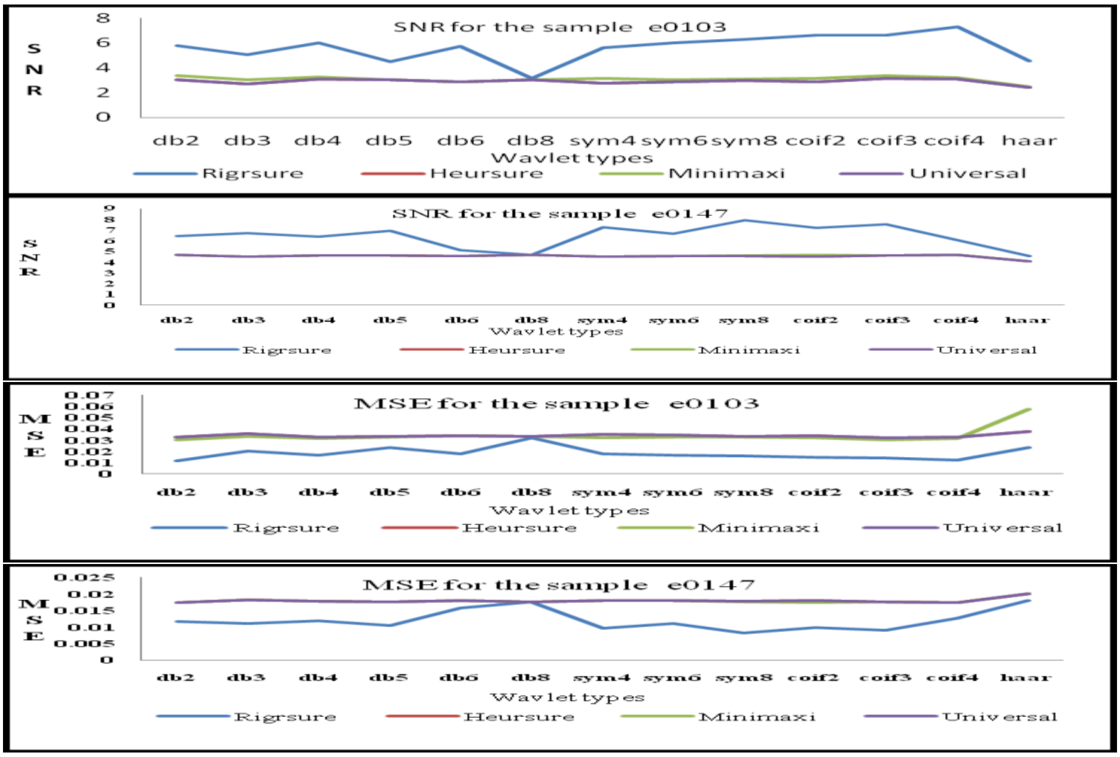

Fig.3. Plot of SNR & MSE for four thresholding rules computed over the 2 ECG Records

TABLE 1: SELECTION OF BEST WAVELET FUNCTION FOR DENOISING THE ECG SIGNAL BASED ON SNR

	SNR												
Datasets	**db2**	**db3**	**db4**	**db5**	**db6**	**db8**	**sym4**	**sym6**	**sym8**	**coif2**	**coif3**	**coif4**	**haar**
e0103	5.7762	5.0762	6.0239	4.5104	5.7386	3.1641	5.6394	6.0135	6.2718	6.6072	6.6246	**7.2835**	4.5641
e0147	6.4127	6.6869	6.3866	6.9524	5.1179	4.6607	7.2831	6.664	**7.9217**	7.2099	7.5279	6.0705	4.5688
e0105	3.5118	4.2839	4.2958	3.8808	4.4404	4.0823	4.3793	4.5109	4.5301	**4.5378**	4.226	3.98	3.7348
e0106	5.2569	4.9227	4.182	4.3169	1.7798	3.164	4.9899	5.1375	4.6782	**5.3669**	4.8255	4.7649	4.7869
e0166	6.1652	6.1821	6.9981	5.0785	4.4598	5.7341	7.0705	7.2097	7.4344	7.9272	6.9907	**8.3264**	4.6339
e0170	6.4684	8.3908	6.7833	4.9509	6.2998	5.4708	6.3739	7.4277	7.5789	7.4468	**9.1738**	8.3305	6.3415
e0108	8.7671	4.7245	7.9511	5.1951	6.7294	6.7136	4.5264	5.3077	8.84	**8.9589**	6.126	8.4401	8.0447
e0119	**4.087**	3.3531	3.5781	3.8996	3.4375	3.8909	3.4091	3.4141	3.4841	3.3393	3.7428	3.9822	2.9996
e0133	6.4279	8.4932	8.1334	5.7202	5.9615	5.7504	7.9271	6.0357	7.9965	**8.515**	8.2536	7.3938	5.669
e0212	5.3607	5.4119	5.0745	5.5461	5.4422	**5.6613**	5.4567	5.3736	5.2951	5.1989	5.198	5.575	4.518
e0304	3.1429	6.3313	4.1956	3.8623	5.9091	4.3213	**6.5382**	5.9649	5.4206	5.6653	3.917	3.9001	4.2708
e0406	4.5493	3.1504	**5.7785**	3.0802	3.2082	3.1159	3.1726	3.197	3.1876	5.4163	3.0891	4.3553	3.0189
e0509	4.1635	4.3964	4.2823	3.7556	2.9535	2.4208	4.3142	4.8252	4.7403	4.1423	2.8718	3.0954	**5.0472**
e0603	**4.604**	3.2657	3.6726	4.4283	3.3767	4.275	3.3002	3.3021	3.417	3.1817	4.0321	4.4758	3.0317
e0801	**3.7235**	3.2972	3.4199	3.648	3.3441	3.5814	3.3277	3.3076	3.3258	3.2554	3.4926	3.6238	2.8702
Ratio of Wavelets in numbers (%)	3 (20%)	0 (0%)	1 (6.7%)	0 (0%)	0 (0%)	1 (6.7%)	1 (6.7%)	0 (0 %)	1 (6.7%)	**4 (27%)**	1 (6.7%)	2(13.3%)	1 (6.7%)

TABLE 2: SELECTION OF BEST WAVELET FUNCTION FOR DENOISING THE ECG SIGNAL BASED ON MSE

	MSE												
Datasets	**db2**	**db3**	**db4**	**db5**	**db6**	**db8**	**sym4**	**sym6**	**sym8**	**coif2**	**coif3**	**coif4**	**haar**
e0103	0.176	0.0206	0.0166	0.0235	0.0177	0.0321	0.0181	0.0166	0.0157	0.0145	0.0144	**0.0124**	0.0232
e0147	0.0117	0.011	0.0118	0.0104	0.0158	0.0176	0.0096	0.0111	**0.0085**	0.0098	0.0091	0.0127	0.018
e0105	0.0128	0.0107	0.0107	0.0108	0.0103	0.0114	0.0105	0.0102	0.0101	**0.0101**	0.0109	0.0115	0.0122
e0106	0.0119	0.0171	0.0203	0.0197	0.0353	0.0257	0.0169	0.0163	0.0181	**0.0155**	0.0175	0.0178	0.0179
e0166	0.0147	0.0146	0.0121	0.0189	0.0218	0.0162	0.0119	0.0115	0.011	0.0098	0.0121	**0.0089**	0.0209
e0170	0.0263	0.0169	0.0245	0.0373	0.0274	0.0331	0.0269	0.0211	0.0204	0.021	**0.0141**	0.0172	0.0271
e0108	0.011	0.028	0.0133	0.0251	0.0177	0.0175	0.0293	0.0245	0.0108	**0.0108**	0.0203	0.0119	0.013
e0119	**0.0093**	0.0111	0.0105	0.0098	0.0108	0.0098	0.0109	0.0109	0.0107	0.0111	0.0101	0.0096	0.012
e0133	0.0147	0.0091	0.0099	0.0173	0.0163	0.0172	0.0104	0.0161	0.0102	**0.0091**	0.0096	0.0117	0.0175
e0212	0.0109	0.0108	0.0117	0.0105	0.0107	**0.0102**	0.0107	0.0109	0.0111	0.0113	0.0113	0.0109	0.0133
e0304	0.0232	0.0111	0.0182	0.0197	0.0123	0.0177	**0.0106**	0.0121	0.0137	0.013	0.0194	0.0195	0.0179
e0406	0.0171	0.0236	**0.0129**	0.024	0.0233	0.0238	0.0235	0.0234	0.0234	0.014	0.0239	0.0179	0.0243
e0509	0.0218	0.0207	0.0212	0.0239	0.0288	0.0326	0.0211	0.0187	0.0191	0.0219	0.0293	0.0279	**0.0178**
e0603	**0.0111**	0.0151	0.0137	0.0115	0.0147	0.0119	0.015	0.0149	0.0146	0.0154	0.0126	0.0114	0.0159
e0801	**0.0061**	0.0068	0.0066	0.0062	0.0067	0.0063	0.0067	0.0076	0.0067	0.0068	0.0065	0.0063	0.0075
Ratio of Wavelets in numbers (%)	3 (20%)	0 (0%)	1 (6.7%)	0 (0%)	0 (0%)	1 (6.7%)	1 (6.7%)	0 (0 %)	1 (6.7%)	**4(27%)**	1 (6.7%)	2 (13.3%)	1 (6.7%)

TABLE 3: SELECTION OF BEST WAVELET FUNCTION FOR DENOISING THE ECG SIGNAL BASED ON PSNR

	PSNR												
Datasets	**db2**	**db3**	**db4**	**db5**	**db6**	**db8**	**sym4**	**sym6**	**sym8**	**coif2**	**coif3**	**coif4**	**haar**
e0103	65.6757	64.9921	65.9297	64.4201	65.6511	63.0658	65.554	65.9297	66.1718	66.5171	66.5472	**67.1966**	64.4759
e0147	67.4489	67.7169	67.412	67.9605	66.1442	65.6757	68.3081	67.6776	**68.5884**	68.2185	68.5404	67.0928	65.5781
e0105	67.0587	67.837	67.837	67.7966	68.0024	67.5618	67.9189	68.0448	68.0876	**68.1308**	67.7565	67.5238	67.2672
e0106	66.1168	65.8008	65.0558	65.1861	62.6531	64.0315	65.8519	66.0089	65.554	**66.2275**	65.7004	65.6266	65.6023
e0166	66.4576	66.4873	67.3029	65.3662	64.7462	66.0357	67.3753	67.5238	67.7169	68.1308	67.3029	**68.6369**	64.9293
e0170	63.9312	65.8519	64.2391	62.4137	63.7533	62.9325	63.8333	64.888	65.0345	64.9086	**66.6695**	65.7755	63.8011
e0108	67.7169	63.6592	66.8923	64.1341	65.6511	65.7004	63.4621	64.2391	67.7966	**67.8777**	65.0558	67.3753	66.9914
e0119	**68.5884**	67.6776	67.9189	68.2185	67.7966	68.2185	67.7565	67.7565	67.837	67.6776	68.0876	68.3081	67.339
e0133	66.4576	68.5404	68.1745	65.7503	66.0089	65.7755	67.9605	66.0625	68.0448	**68.5884**	68.3081	67.4489	65.7004
e0212	67.7565	67.7966	67.4489	67.9189	67.837	**68.1308**	67.837	67.7565	67.6776	67.6	67.6	67.7565	66.8923
e0304	64.4759	67.6776	65.5301	65.1861	67.2318	65.6511	**67.7169**	67.3029	66.7636	66.9914	65.2528	65.2305	65.6023
e0406	65.8008	64.4017	**66.9914**	64.3287	64.4572	64.365	64.4201	64.4386	64.4386	66.6695	64.3468	65.6023	64.2747
e0509	64.7462	64.9711	64.8674	64.3468	63.5369	62.9986	64.888	65.4124	65.3205	64.7264	63.4621	63.6748	**65.5781**
e0603	**67.7169**	66.341	66.7636	67.5238	66.4576	67.3753	66.3699	66.3989	66.4873	66.2556	67.1271	67.5618	66.1168
e0801	**70.3493**	69.8057	69.9354	70.2069	69.8701	70.1374	69.8701	69.3227	69.8701	69.8057	70.0017	70.1374	69.3802
Ratio of Wavelets in numbers (%)	3 (20%)	0 (0%)	1 (6.7%)	0 (0%)	0 (0%)	1 (6.7%)	1 (6.7%)	0 (0 %)	1 (6.7%)	**4(27%)**	1 (6.7%)	2 (13.3%)	1 (6.7%)

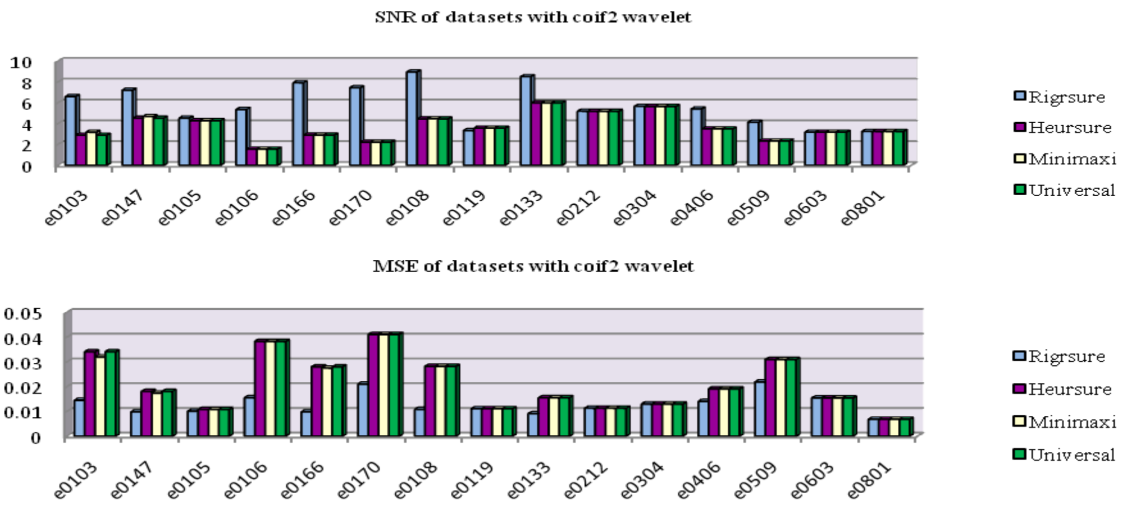

Fig.4. Comparison of SNR & MSE of datasets with four thresholding rules and ‘COIF2’ Wavelet function

Fig (4) shows a comparison chart of SNR & MSE of datasets with four thresholding rules and using “COIF2” wavelet function. From the chart, it is inferential that rigrsure thresholding rule has shown improved results in terms of SNR & MSE on all the datasets.

IV. Conclusion

This paper describes the wavelet based ECG signal denoising using 13 wavelet functions and 4 thresholding rules. In this study, experiment is conducted by randomly choosing the 15 ECG records from ST-T change datasets of physionet database. The performance of ECG signal denoising is evaluated by considering measures SNR, MSE and PSNR. On the whole, ‘coif2’ wavelet function and ‘rigrsure’ gives the best performance in comparison with other wavelet functions and threshold rules. The conclusion can be drawn from the experimental results that the wavelet function ‘coif2’ and threshold rule ‘rigrsure’ gives the optimum performance for ECG signal denoising.

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