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Research Article

Denoising of Biological Signals using Wavelets

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Abstract

Methods based on thresholding of wavelet coefficients have been found to be popular in the estimation of biological signals from noisy environment. Hard and soft filters are most commonly used in these methods. In this paper a novel thresholding filter for wavelet shrinkage estimation of biological signals is proposed. The proposed novel filter is applied using Visu Shrink rule and top rule to denoise ECG signal contaminated with additive white Gaussian noise. The performance of the filter is compared with that of hard and soft filters. Mean Square Error (MSE) and Signal to Noise Ratio (SNR) are used as criteria for testing the performance of denoising. From the simulation results it is found that the novel filter performs better than soft filter with Visu rule and hard filter with top rule.

Key-Words: *ECG, Wavelet transform, Wavelet thresholding, Wavelet shrinkage, Novel thresholding filter, Denoising*

1. Introduction

Nowadays there has been phenomenal growth in the collection of signals or data. During signal acquisition or transmission it is often contaminated with noise. Denoising is a main problem that must be addressed before carrying out any further analysis of signal or data.This is applicable to biological signals also.Various techniques have been suggested for denoising of biological signals. Wavelet transform has been proved to be a successful tool for analysis of biological signals because of its good localization properties in time and frequency domain (B.Vidakovic *et al*, 1999). In this paper, wavelet shrinkage denoising of biological signals is considered and novel thresholding filter is proposed for this (A.Bruce *et al*, 1996). The performance of the proposed new filter is evaluated by using Visu shrink rule and top rule in denoising of ECG signals corrupted with additive white Gaussian noise. The results are compared with that of widely used hard and soft filters. MSE and SNR are used to test the quality of denoising (D.L.Donoho *et al* 1995).

2. Denoising using Wavelet Shrinkage

In wavelet shrinkage denoising of biological signals, first the noisy signal is decomposed into wavelet coefficients by using Wavelet transform. After fixing the threshold using a thresholding rule, the coefficients are filtered by using a thresholding filter. Denoised signal estimate is obtained by using inverse wavelet transform on the modified wavelet coefficients (Carl Taswell *et al*,2000). Visu shrink (Universal) thresholding rule and top thresholding rule are considered in this paper. In this denoising method wavelet Symmlet 8 is considered for forward and inverse transformations (I.Daubechies *et al*, 1992).

2.1 Visu Shrink

Universal threshold for a signal of length N is given by $\hat{\sigma}\sqrt{2\log N}$, where $\hat{\sigma}$ is the estimate of noise standard deviation (D.L Donoho *et al*, 1994). Visu Shrink is thresholding performed by applying this threshold. This is global thresholding scheme and threshold is determined independently of the thresholding filter.

2.2 Top rule

Top rule is a global thresholding method and it is independent of thresholding function selected. Given p as the fraction of the largest coefficients to keep, the threshold is set to be the (1-p)th quantile of empirical distribution of absolute values of wavelet coefficients (I.K.Fodor *et al*, 2003).

2.3 Thresholding Filters

The thresholding filters determine how the threshold is applied. The most popular hard and soft filters are considered in this paper (Figs 1 and 2).

Donoho and Johnstone proposed hard thresholding filter which is defined as given below (Marteen Jansen, 2001)

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$$H(\omega,\lambda) = \omega \quad for\ all\ |\omega| > \lambda$$
$$= 0 \quad otherwise$$

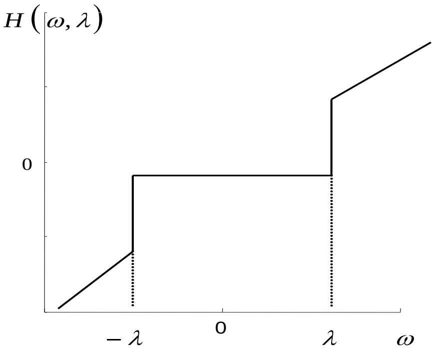

Fig. 1 Hard Thresholding Filter

Algorithm for Soft thresholding filter is as follows (Donoho, D. L, 1995)

$$S(\omega,\lambda) = sgn(\omega)(|\omega| - |\lambda|) \quad for\ all\ |\omega| > \lambda$$
$$= 0 \quad otherwise$$

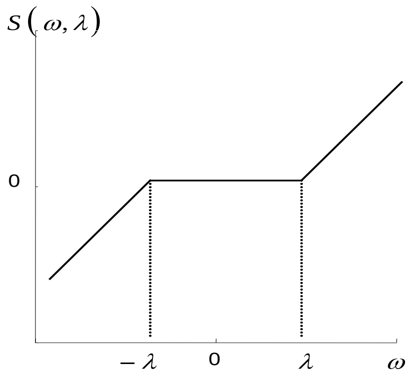

Fig. 2 Soft Thresholding Filter

ω represents detail wavelet coefficients, λ represents the threshold

3. Novel Thresholding Filter

In this paper a novel thresholding filter is proposed for filtering the noisy wavelet coefficients. The proposed novel filter is designed by taking the average of outputs of hard and soft thresholding filters and it is given by

$$N(\omega,\lambda) = \frac{sgn(\omega)[\omega + (|\omega| - |\lambda|)]}{2} \quad forall\ |\omega| > \lambda$$
$$= 0 \quad otherwise$$

ω Represents detail wavelet coefficients, λ represents the threshold.

When $|\omega| > \lambda$ for each input wavelet coefficient, this new filter performs filtering operation by taking the average of outputs of hard and soft filters on the wavelet coefficients. When $|\omega| < \lambda$ the filter rejects the wavelet coefficients.

4. Simulation Results and Discussion

This section reports the results obtained on denoising of ECG signals using hard, soft and novel thresholding filters. ECG signals of sample size 2048 contaminated with additive white Gaussian noise of different values of standard deviation (σ) are simulated. Wavelet decomposition of ECG signal is made using Symmlet 8 (S.G.Mallat *et al*,1989). After fixing the threshold using Visu Shrink rule and Top rule the wavelet coefficients are filtered by using a thresholding filter. The inverse wavelet transform is applied on the resultant coefficients and denoised signal estimate is obtained (R.T. Ogden 1997).
MSE and SNR are used as measure of denoising. They are calculated as given below

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(X(i) - \hat{X}(i)\right)^2$$

$$SNR = 10\log_{10}\frac{\sum_{i=1}^{n}X(i)^2}{\sum_{i=1}^{n}\left(X(i) - \hat{X}(i)\right)^2} \text{ dB}$$

n Represents no. of samples, *X(i)*original signal data, *X(i)* denoised signal data The simulation experiment is repeated 100 times and average values of MSE and SNR are found. These experiments are conducted on 50 numbers of ECG signals and found that the results are same. The simulation is implemented in MATLAB environment. Denoising results of ECG signal obtained using hard, soft and novel thresholding filters for σ=10, 20 and 30 using Universal (Visu) rule and top rules are given in tables 1 and 2. The original and denoised signals of ECG obtained using hard, soft and new thresholding filters with Universal rule and top rule are shown in Figs 3-10.

For a noisy signal of σ =10, using universal rule, MSE of 51.38 and SNR of 25.19 are obtained on denoising with hard thresholding filter and MSE of 192.96 and SNR of 19.44 with Soft thresholding filter (Table1). For novel filter for σ =10, MSE of 84.87 and SNR of 23.01 are found. This indicates that the new filter performs better than soft thresholding filter. The same behavior of new thresholding filter is noticed for σ =20 and 30 (Table1).
Results of denoising of ECG signal of length 1024 using Top rule are reported in table 2. For a noisy signal of σ =10, MSE of 74.58 and SNR of 23.57 are obtained on denoising using hard thresholding filter and MSE of 49.40 and SNR of 25.36 with soft thresholding filter(Table2). For novel filter for σ =10, MSE of 48.59 and SNR of 25.43 are found. This indicates that the new filter performs better than hard thresholding filter. The same behavior of new thresholding filter is observed for σ =20 and 30 (Table 2).

Table 1: Denoising Results of ECG signal using Hard, soft and Novel Thresholding filters :universal rule, length: 2048

	σ =10		**σ =20**		**σ =30**	
	MSE	SNR	MSE	SNR	MSE	SNR
Noisy Signal	99.91	22.3	399.01	16.28	896.98	12.76
Hard filter	51.38	25.19	166.41	20.09	326.93	17.16
Soft filter	192.96	19.44	528.57	15.07	939.26	12.57
Novel filter	**84.87**	**23.01**	**252.12**	**18.28**	**463.06**	**15.65**

Table 2: Denoising Results of ECG signal using Hard, Soft and Novel Thresholding filters:Top rule, length: 2048

	σ =10		**σ =20**		**σ =30**	
	MSE	SNR	MSE	SNR	MSE	SNR
Noisy Signal	99.92	22.3	400.87	16.26	897.3	12.76
Hard filter	74.58	23.57	299.87	17.52	676.6	13.99
Soft filter	49.4	25.36	146.33	20.64	286.3	17.73
Novel filter	**48.59**	**25.43**	**175.18**	**19.86**	**385.87**	**16.43**

Fig. 3 Original ECG

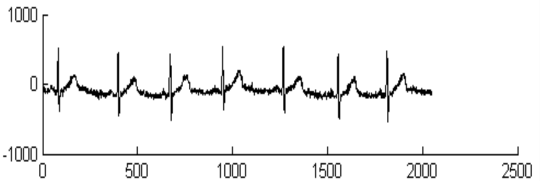

Fig.4 Noisy ECG

Fig. 5 Denoised ECG using hard filter with Visu rule

Fig. 6 Denoised ECG using soft filter with Visu rule

Fig. 7 Denoised ECG using novel thresholding filter with Visu rule.

Fig. 8 Denoised ECG using hard filter with top rule

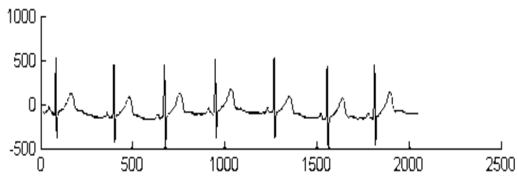

Fig. 9 Denoised ECG using soft filter with top rule

Fig. 10 Denoised ECG using novel thresholding filter with top rule

5. Conclusion

A novel thresholding filter for wavelet shrinkage denoising of biological signals is proposed in this paper. The performance of this filter is evaluated by using ECG signals. The results are compared with the existing hard and soft filters. It is found that it performs better than soft filter with Visu rule and superior to hard filter with top rule.

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