# Non Parametric Regression of Biological Signals using Wavelets

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***Abstract*** **- To estimate the biological signals from noisy environment wavelet shrinkage method is popularly used. In this method hard and garrote filters are commonly used. A hybrid thresholding filter is proposed in this paper to estimate the biological signals. This hybrid filter is applied to noisy EEG signal contaminated with additive white Gaussian noise using FDR method and Hypothesis method. These results are compared with existing hard and garrote filters and also compared with Block James stein method using Mean square error (MSE) and Signal to noise ratio (SNR) parameters. From the results, the hybrid thresholding filter performs better than both hard and garrote filters with FDR method and Hypothesis method and also performs better than existing Block James stein method.**

***Keywords: Wavelet Transform, EEG signal, Wavelet shrinkage method, Denoising, hybrid thresholding filter***

## 1. INTRODUCTION

In present days there has been phenominal growth in collection of signals or data. During the transmission, it is contaminated with noise. Before processing the signal at the destination, denoising is required. This is applicable to biological signal also. The random noises uncorrelated with biological signals can be approximated by additive gaussian noise There are so many methods for denoising the signal, Wavelet transform is very popular method because of its good localization properties of time and frequency domain.

Wavelet shrinkage denoising is widely used technique for denoising of biological signal and a hybrid thresholding filter is proposed in this paper. This filter is evaluated by using FDR method and Hypothesis method to denoising the EEG signal. These results are compared with existing filters and Block James stein method using MSE and SNR parameters.

## 2. WAVELET SHRINKAGE DENOISING

In this method, first the noisy EEG signal is applied to Wavelet transform to get wavelet coefficients. After fixing the threshold value using thresholding method, the wavelet coefficients are modified subjecting to threshold value using a thresholding filter. The inverse wavelet transform is applied on modified wavelet coefficients to get the denoised EEG signal. In this paper, FDR method, Hypothesis method and Block James stein method are proposed and coiflet wavelet is used in wavelet transform and inverse wavelet transform.

*2.1 FDR method*

The minFDR (minimizing false discovery rate) method was introduced by B. Vidakovic for one-dimensional data. It determines the same global threshold for all shrinkage functions by keeping the expected value of the fraction of coefficients erroneously included in the reconstruction below a given fraction *p*. Given the M wavelet coefficients ($\omega_n$, n = 1, 2... M), first it computes x-values.

$$x_n=2[1-\Phi\ (|w_n|/\sigma)]$$

Where $\Phi$ (.) is the cumulative distribution function of the standard normal distribution and $\sigma$ is an estimation of the noise-standard deviation. Then $x_n$ values are ordered as $x_{(1)}\leq x_{(2)}\leq x_{(3)}\ldots.\leq x_{(M)}$. Starting with n = 1, let q be the largest index such that

$$x_{(q)}\leq \frac{q}{M}p$$

The threshold value is obtained as

$$\lambda=\sigma\ \Phi^{-1}(1-(x_{(q)}/2))$$

*2.2 Hypothesis method*

The threshold estimation in this method is independent of thresholding filter used. It calculates level dependant thresholds after performing wavelet transformation on the signal (Ogden, 1997).

Let the wavelet coefficients $\omega$ are M in number at a particular level and assume that they are normally distributed.

$$V^{\delta}_{M}=\{\Phi^{-1}[((1-\delta)^{1/M}+1)/2]\}^{2}$$

$\Phi$ ( ) is cumulative distribution function of standard normal density. Where $\delta$ is error probability parameter. Then find the largest of the squared wavelet coefficients at that level, denoted by $\omega^2{}_{(M-1)}$ and compare it to the above value $V^{\delta}_{M}$. If

$$\omega^2{}_M/\sigma^2> V^{\delta}_{M}$$

Where, $\sigma$ is an estimate of the standard deviation of noise, $\omega^2_M$ is retained as signal. Next repeat the process with the square of second largest (in absolute value) wavelet coefficient $\omega^2_{(M-1)}$. If

$$\omega^2_{(M-1)}/\sigma^2 > V^{\delta}_{M-1}$$

The procedure continues until at some point the bth largest (in absolute value) coefficient satisfies

$$\omega^2_{(b)}/\sigma^2 > V^{\delta}_{b}$$

The threshold at that level is then set as $\lambda = \alpha\, \omega^2_{(b)}$. The recommended value for $\delta$ is 0.05.

*2.3 Block James stein method*

Block James stein method was proposed by CAI (1999). It is also a thresholding method containing blocks but in this thesholding filter is not used. Fix a block size L and a threshold level λ and divide the empirical wavelet coefficients $\omega_{i,k}$ at any given resolution level j into nonoverlapping blocks of size L. In each case, the first few empirical wavelet coefficients might be re-used to fill the last block which is called the *Augmented* case or the last few remaining empirical wavelet coefficients might not be used in the inference which is called the *Truncated* case, should L not divide 2^j exactly.

Denote (jb) the indices of the coefficients in the b-th block at level j, i.e. (jb) = {(j, k): (b − 1) L + 1 ≤ k ≤ bL}.Let $S^2_{ib} = \Sigma_{k\in(ib)}\omega^2_{i,k}$ denote the sum of squared empirical wavelet coefficients in the block. A block (jb) is deemed important if $S^2_{ib}$ is larger than the threshold λ and then all the coefficients in the block are retained otherwise the block is considered negligible and all the coefficients in the block are estimated by zero.

*2.4 Thresholding Filters*

Thresholding filters are used to apply the threshold value. In this paper Hard and Garrote filters are consider.

Hard filter is proposed by Donoho and Johnstone and it is defined as

$$H(\omega,\lambda) = \omega \text{ for } |\omega| > \lambda$$
$$= 0 \text{ otherwise}$$

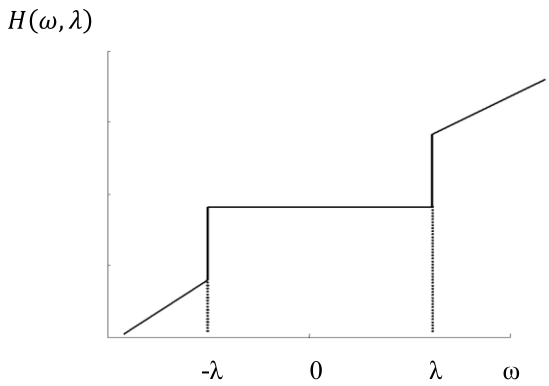



Fig. 1 Hard Thresholding Filter

Garrote filter is defined as

$$G(\omega,\lambda) = \left(\omega - \frac{\lambda^2}{\omega}\right) \quad \text{for all } |\omega|>\lambda$$
$$= 0 \qquad \text{otherwise}$$

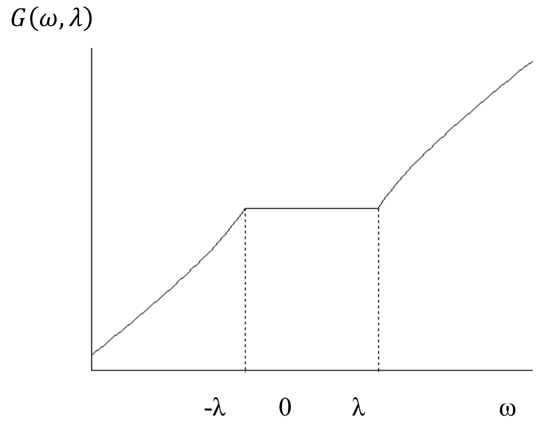



Fig. 2 Garrote Thresholding Filter

ω represents wavelet coefficients and λ represents threshold value

## 3. HYBRID THRESHOLDING FILTER

For filtering the noisy wavelet coefficients, the hybrid thresholding filter is proposed in this paper. This filter is designed by taking the average of outputs of Garrote and Hard thresholding filters for above threshold value. For below threshold value, 20 % of coefficient value is considered. It is represented as

$$H(\omega,\lambda) = \frac{\left(\omega - \frac{\lambda^2}{\omega}\right) + \omega}{2} \quad \text{for all } |\omega| > \lambda$$
$$= 0.2*\omega \qquad \text{otherwise}$$

ω represents wavelet coefficients and λ represents threshold value.

## 4. SIMULATION RESULTS AND DISCUSSION

In this section the results obtained using hard, garrote and hybrid thresholding Filter on noisy EEG signal are presented. The EEG signal of sample size is 2048 and it is contaminated with white Gaussian noise of different standard deviation values are simulated. Wavelet transform with coiflet wavelet is used to decompose the EEG signal. FDR method and Hypothesis method are used to fix the threshold value. Wavelet coefficients are modified using a thresholding filter. The inverse wavelet transform is applied on modified wavelet coefficients. The results are compared using MSE and SNR parameters.

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

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

n represents no.of samples, $S(i)$ is original signal and $\hat{S}(i)$ is denoised signal. The simulation experiment is repeated 100 times and average values of MSE and SNR values are taken. This process is conducted on different EEG signals and the results are same. This simulation is implemented in MATLAB environment. The results of EEG signal for σ=10, 20 and 30 using hard, garrote and hybrid thresholding filter with FDR method and Hypothesis method are shown in Table 1 and Table 2. Table 3 indicates the denoising results of EEG signal using Block James stein method. The original and denoised EEG signals using hybrid thresholding filter with FDR method and Hypothesis method are shown in Figs 3-6. Fig 7 shows denoised signal of EEG signal using Block James stein method. Graph 1-6 shows the comparision of the results in FDR, Hypothesis and Block James stein methods.

For σ =10, MSE is 60.3710 and SNR is 17.8923 are obtained on denoising of noisy EEG signal with hard thresholding filter and MSE is 70.9529 and SNR is 17.1982 are obtained with garrote thresholding filter using FDR method. For hybrid thresholding filter, MSE is 48.2747 and SNR is 18.8645 are obtained (Table 1). This indicates that the hybrid thresholding filter performs better than both hard and garrote thresholding filters. The same behavior is found for σ =20 and 30 (Table 1).

Using Hypothesis method, for σ =10, MSE is 69.1445 and SNR is 17.3054 are obtained on denoising of noisy EEG signal with hard thresholding filter and MSE is 86.1091 and SNR is 16.3554 are obtained with garrote thresholding filter. For hybrid thresholding filter, MSE is 55.2715 and SNR is 18.2779 are obtained (Table 2). This indicates that the hybrid thresholding filter performs better than both hard and garrote thresholding filters. The same behavior is found for σ =20 and 30 (Table 2) .

Using Block James stein method, for σ =10, MSE is 60.1850 and SNR is 17.9113 are obtained on denoising of noisy EEG signal (Table 3). It is clear that the MSE and SNR values of hybrid thresholding filter using FDR method and Hypothesis method are better than Block James stein method. For σ =20 and 30 also the same result obtained.

Table 1: Denoising Results of EEG signal using Hard, garrote and hybrid Thresholding Filters: FDR method

| | σ =10 | | σ =20 | | σ =30 | |
|---|---|---|---|---|---|---|
| | MSE | SNR | MSE | SNR | MSE | SNR |
| Noisy signal | 100.4997 | 15.6767 | 397.6322 | 9.7044 | 899.4194 | 6.1594 |
| Hard filter | 60.3710 | 17.8923 | 164.2737 | 13.5472 | 291.6928 | 11.0574 |
| Garrote filter | 70.9529 | 17.1982 | 191.9717 | 12.8735 | 355.9487 | 10.1958 |
| Hybrid filter | 48.2747 | 18.8645 | 135.8736 | 14.3714 | 249.6676 | 11.7317 |



Table 2: Denoising Results of EEG signal using Hard, garrote and hybrid Thresholding Filters: Hypothesis method

| | σ =10 | | σ =20 | | σ =30 | |
|---|---|---|---|---|---|---|
| | MSE | SNR | MSE | SNR | MSE | SNR |
| Noisy signal | 100.4997 | 15.6767 | 397.6322 | 9.7044 | 899.4194 | 6.1594 |
| Hard filter | 69.1445 | 17.3054 | 166.2564 | 13.4932 | 278.9246 | 11.2512 |
| Garrote filter | 86.1091 | 16.3554 | 199.8411 | 12.6974 | 334.6151 | 10.4638 |
| Hybrid filter | 55.2715 | 18.2779 | 138.8248 | 14.2779 | 242.9398 | 11.8502 |

Table 3: Denoising Results of EEG signal: James stein method, length: 2048

| | σ =10 | | σ =20 | | σ =30 | |
|---|---|---|---|---|---|---|
| | MSE | SNR | MSE | SNR | MSE | SNR |
| Noisy signal | 100.4997 | 15.6767 | 397.6322 | 9.7044 | 899.4194 | 6.1594 |
| Denoised signal | 60.1850 | 17.9113 | 157.7887 | 13.7248 | 273.7316 | 11.3370 |

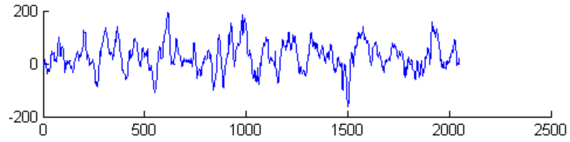



Fig 3: Original EEG signal

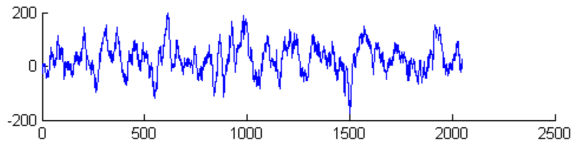



Fig 4: Noisy EEG signal

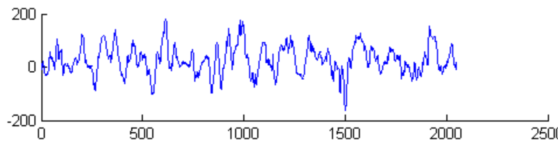



Fig 5: Denoised EEG signal using hybrid thresholding filter with FDR method

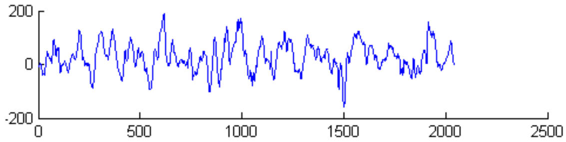



Fig 6: Denoised EEG signal using hybrid thresholding filter with Hypothesis method

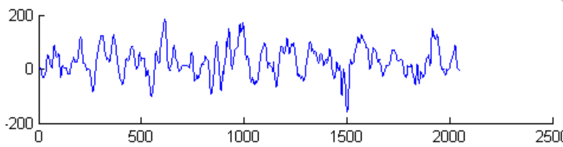
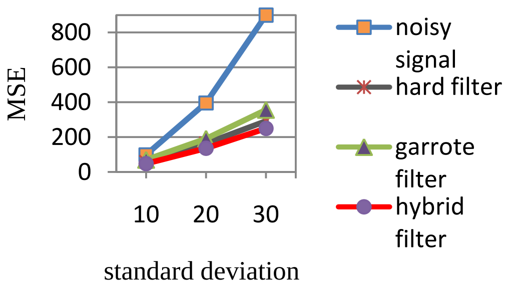
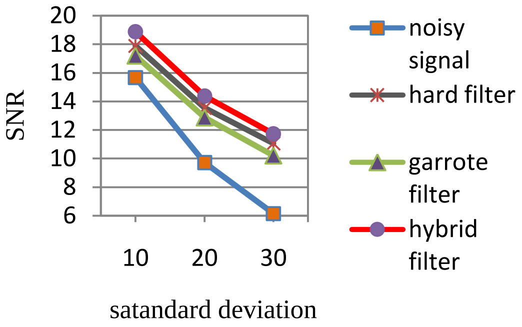


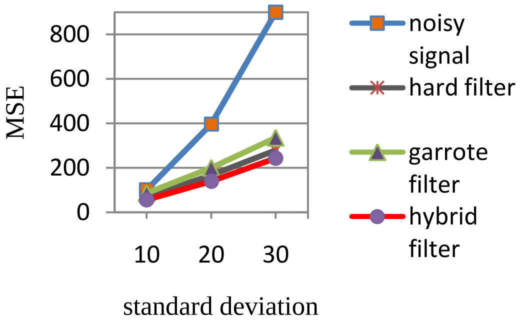

Fig 7: Denoised EEG signal with James Stein method



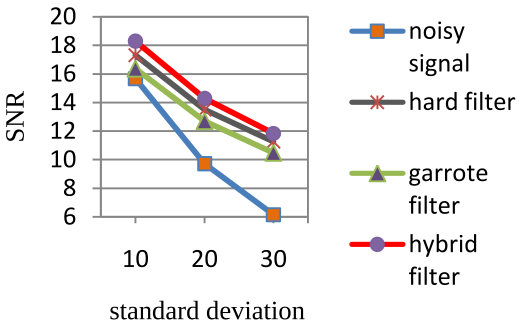

Graph 1: MSE values of different filters in FDR method.



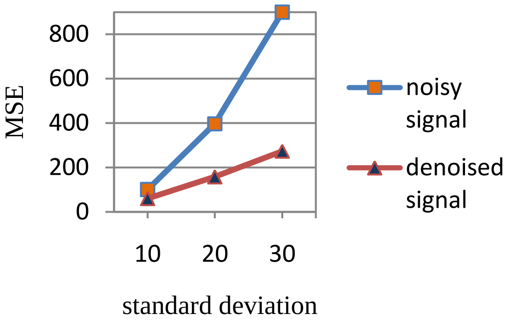

Graph 2: SNR values of different filters in FDR method.



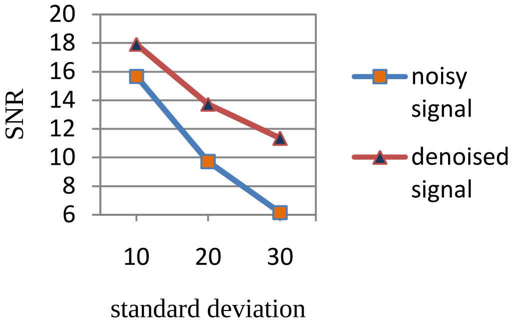

Graph 3: MSE values of different filters in Hypothesis method




Graph 4: SNR values of different filters in Hypothesis method




Graph 5: MSE values in Block James stein method




Graph 6: SNR values in Block James stein method.

## 5. CONCLUSION

In this paper, a hybrid thresholding filter for wavelet shrinkage denoising of Biological signals is proposed. The performance of this filter is evaluated by using EEG signals. The results are compared with existing hard and garrote filters and Block James stein method. It is found that the hybrid thresholding filter performs better than both hard and garrote filters with FDR method and Hypothesis method and also performs better than existing Block James stein method.

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