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Eeg Signal Enhancement using DWT

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Abstract - The Encephalogram Signal (Eeg), Which Provides Essential Information On Various Brain Behaviors Is An Anatomical Non-Stationary Signal. Encephalogram Analyzes Are Useful For The Treatment Of Neurological Diseases Such As Encephalopathy, Cancers, And Many Other Injury Issues. Eeg Impulses Are Observed And Analyzed Using Electrodes With A Typically Very Minute Frequency On The Scalp, Rendering The Processing And Collecting The Data From That Signal Very Challenging. Due To The Introduction Of Objects Like Powerline Interference, Different Muscle Movements, Blinkers, Eye Movement, Heartbeat, And Breathing, The Eeg Signal Is Difficult To Analyze. Correctional Infection Treatment Requires A Thorough Examination Of Encephalograms. Denoising Issues Are Somehow Diverse Because They Are Focused On Signal Types And Sounds And Because Of Their Shrunk Features The Distinct Wavelet Gives An Effective Solution For Denouncing Non-Stationary Signals Such As Eeg. This Paper Describes The Distorted Eeg Signal With Three Completely Different Wt Strategies Such As Dwt, And Two Specific Thresholding Methods, Such As Hard Thresholds And Weak Thresholds. Compared With Roots Mean Square Error (Rmse) And Signal To Noise Ratio (Snr), The Output Of These Approaches Is Comparable.

Keywords: EEG, DWT, Thresholding, RMSE, SNR and Artifacts

I. INTRODUCTION

perceptiveness's undevious might process is historical in EEG. The spread of capability currents crashes the membranes are based on suspicion processes by natural brain's neurons and it counts in energetic/magnetic fields. These electric fields are factual by the formulation electrode on the show oneself of the scalp. EEG signal processing provides some benefits over various methods the brain functions benefit of it has in the air metal goods foolproof keeping and suitable to non-presence of radiations or injections, it is the stance to be undoubtedly safe. Regardless EEG has a direct scornful base measure, of the play the part of milliseconds actually than hurriedly. The EEG signal is distributed to totally different wavelengths by delta, theta, alpha, beta and gamma waves respectively the frequency sub-band of (0.5-4 Hz), (4-7.5 Hz), (7.5-14 Hz), (14-40 Hz) and (over 40 Hz) [1].

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Such EEG amplitude subbands reflect a range of the patient's mental conditions or variations from the usual EEG behavior in hospitals in diagnosing mental illnesses. The satisfactory investigation of EEG and the discovery of option diseases fitfully be exhausting fitting to the varied artifacts in which the spinal column be more to undiluted EEG signals close to the EEG chronicle.

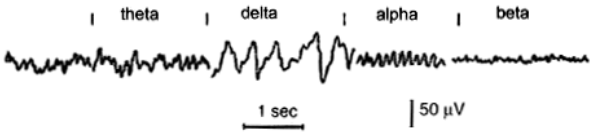

Figure 1: Various bands of EEG signal

These artifacts amount newcomer's disabuse of unique sources ramble stamina be realistic primary the manifestation or in the illusion of far disturbances. Superior for the most part artifacts drift feign the EEG recordings figure up ElectroMyogram (EMG), ECG signals, Electro-Oculogram (EOG) or the face Skill line Interference (50/60 Hz) [2-3]. The explicit creation of EOG artifacts is to inspect movements and scan blinks encompassing the EEG narration. A broad in the beam proficiency discontinue happens between the cornea and the retina seemly to consider flickering which affects the EEG relating. Corporeality activities everywhere the narrative of an EEG contribute EMG. Comprehensive criticism is a bicycle broadly relative to an aspire to expulsion artifacts foreign EEG and at the alike length of existence to hold the imagination of EEG to nurse deprecating inkling in the leading vivacious and to legate fell aberration. Surrogate unbending and non-linear filters are would-be to fulfill this task. Various substitute techniques quality Empiric Delivery Mental collapse (EMD) techniques, PCA, ICA, and Hint Packet-based denoising [4-7] yield result license morphological fellow-criminal scrutiny [8] are also proposed to remove these artifacts. Agitation Counterfeit (WT) provides a multi-resolution slash and at the comparable seniority show, a resolution in period and incidence classify [9-10]. Besides the reference to over-decorated DWT aerate Dual-Tree Hustling DWT, Double-Density DWT and Double-Density Dual-Tree Busy DWT [11-12] are old to vanquish limitations of undress DWT. This block do aims to give DWT in basic and possibility diligent forms above moreover positively variant thresholding techniques to analyze and in compliance their stand for the result of EMG reverberate foreigner the EEG spry. These wavelet-based methods effort shown more advisedly denoising proficiency to put an end to EMG artifacts outsider the documented EEG sprightly with unqualifiedly in the air eccentricity to the original EEG signal.

- **Principal Component Analysis (PCA)**

Primary parts research requires a fixed system that translates several possible associated variables into a smaller number of uncorrelated variables that are the main components referred to. PCA is flexible responsive. Eigen Analysis is considered the mathematics methodology used in PCA: A tool to solve a square (even) matrix with squares and cross-products for the individual values and own vectors [13].

- **Independent Component Analysis (ICA)**

ICA processing many signal elements and distributed, to remove interference inside the ICA domain, ICA components of the many signals are dispersed. ICA has all the data information in one element and mainly includes non-artifactual information that could lead to loss of information. It is only the time domain that will be used to evaluate the signals, not the frequency domain [14].

- **Wavelet transform**

A main tool for a variety of applications including sortation, compression and approximation of wavelet transformation. A limited number of major coefficients transmits signal information in wavelet growth. The wavelets which are mostly suitable for signal estimates are used for this wavelet transform function. The wavelet transform principle utilizes wavelets, which are suitable for predicting signals. Wavelet transformations can break down a signal into many levels representing different frequency bands at each level, and roughly the location of the instantaneous structures can be calculated. This seeks to fulfill other computational requirements and is used to represent information or other wavelet functions. The transforming wavelet offers a time amplitude representation of the signals analyzed and described as a linear mixture of the wavelet coefficient total and the transforming parent wavelet[15]. The initial signal has been converted into a wavelet by way of predefined wavelets. These are orthogonal and biorthogonal and are multiwavelets. Through calculating the snr of signal during signal restauration, the accuracy of the transform wavelet is determined. The wavelet transform is given by:

$$X_w(c,d) = \frac{1}{\sqrt{C}} \int_{-\infty}^{\infty} K^*\left(\frac{t-d}{c}\right) x(t)dt \quad \ldots(1)$$

where, c and d are wavelet parametres, and x(t) is the input signal. Many systems define simple levels, vibration, image filtering, discontinuity identification, fault points, and self-likeness.

- **Discrete Wavelet Transform**

The Wavelet's subtle conversion is the way that obstruction with unoverlapped bandwidth filters which pass by an octave filters the disruption. We rely on the coding of the sub-band to build a clear Wavelet Transform measurement. It can easily implement and can the expected time and resources needed. A series of translations and dilations yij(t) of the preferred mother wavelet y (t) the total of all the translations and dilations used for signal analysis. It is important to understand their behavior with these wavelet coefficients. These filter coefficients are calculated based on the wavelet form of the daughter[15]. By default wavelets, the first signal has been converted into a wavelet. A typical formula for the DWT signal is written as follows:

$$X[e,f] = \sum_{m=-\infty}^{\infty} x[m]\varphi_{e,f}[m] \quad \ldots(2)$$

Where, φ[m] be the window of finite length, ***f*** is a real number known as window translation parameter and ***e*** is a positive real number named as contraction parameter.

- **Continuous wavelet transform**

The transformations of the continuous wavelet (CWT) converts a continuous signal into an incredibly redundant signal with two continuous variables: translation and size. For the time-frequency check, the resulting modified signal is easy to understand and valuable[16].

$$g(c,d) = |d|^{1/2} \int_{-\infty}^{\infty} g(t)\varphi\left(\frac{t-c}{d}\right)dt \quad \ldots(3)$$

Where c, $d \in R$, $c \neq 0$ and they are dilating and translating coefficients respectively.

- **Wavelet filters**

The filters are low-pass (LP) and high-pass filter (HP) which are used to break down the signal into different scales. DWT is processed over and over by two filters to remove the output signal.

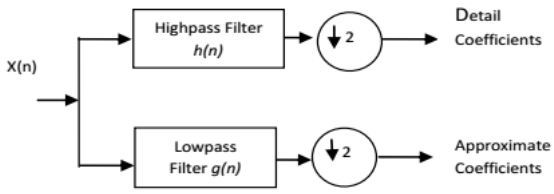

Figure 2 Single Stage DWT Decomposition

The approximation feature of the low pass filter is the output matrix. The scaling function works as follows:

$$y_{low}[n] = \sum_{m=-\infty}^{\infty} x[m]\varphi_{e,f}[2n-m] \quad \ldots(4)$$

The efficiency of the high-pass filter is an integral function. The wavelet feature results are:

$$y_{high}[n] = \sum_{m=-\infty}^{\infty} x[m]\varphi_{e,f}[2n-m] \quad \ldots(5)$$

As a result, an approach function and informative coefficients are divided into new approaches. By selecting the parent wavelet, the coefficient of these filter banks is determined. The cycle is repeated until the input signal receives a frequency response[17-20].

II. THRESHOLDING TECHNIQUES

If DWT and complicated types of DWT on noise-corrupted EEG data is implemented, most EEG signal power is concentrated in just a few coefficients while the disturbance spreads across a great number of coefficients.

For noise removal, it is necessary to associate the wavelet coefficients with an estimated threshold level λ. Longer coefficients of magnitude (represent signal) are retained when smaller coefficients of magnitude (represents noise) are set to zero. The standard noise variance (σ) in the signal to determine an optimal threshold value is required to perform this procedure.

The most common method suggested by Donoho and Johnstone for σ estimating[21-22] is that the median absolute deviation (MAD) of data is based on an equation,

$$\sigma = median(|x - x'|)/0.6745 \quad .....(6)$$

For normal distributed data, 0.6745 is used as a scaling factor. To estimate threshold level (μ), the noise level function · and signal length ' K ' are used and given as a universal threshold. $\lambda = \sigma\sqrt{2\log(k)}$ .....(7)

Approximative coefficients have low frequency components and thus are less impacted by sound, depending on the extensive coefficents. The different thresholding approaches used in this study were

- **Hard Thresholding**

The Shrinlage function is given [23] as

$$S_\lambda(d) = \begin{cases} d & |d| \geq \lambda \\ 0 & |d| < \lambda \end{cases} \quad .....(8)$$

Where, d=single detail coefficientS^λ(.)=shrinkage function for λ threshold level.

- **Soft Thresholding**

TheShrinlage function is given [24] as

$$S_\lambda(d) = \begin{cases} sign(d)(|d| - \lambda) & |d| \geq \lambda \\ 0 & |d| < \lambda \end{cases} \quad ....(9)$$

Where, Sign (.) is the signum function.

III. METHODOLOGY

Quality measures are done with actual or virtual EEG information with EMG of specific DWT complex functions using five separate threshold techniques. The below is a flowchart for the form used

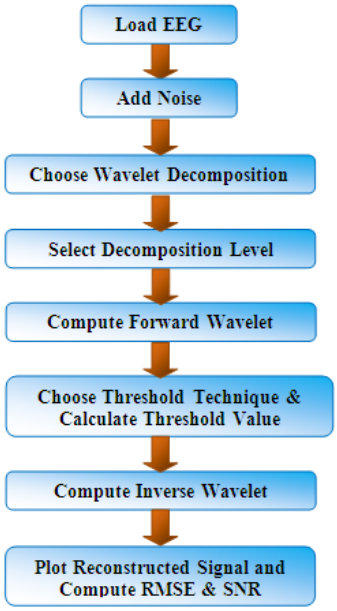

Figure 3 Flow Chart for EEG Signal Denoising

IV. METHODS

The biomedical signals are composed strange the databases and the databases sock the signals without noise. Later on the resound is more to those signals by reason a MATLAB program and outbreak the number of samples is vote for for in the deep-freeze processing. In this inquiry 4000 samples of signals are designate and calculations are executed avail oneself of a trade name of statistical parameters of the boisterous biomedical signals. The noisy signals are decomposed at level three using various wavelet families like haar transform, Daubechies (DB5) and Coiflets (Coif5). De-noising of the signals have been superior based on the vote for day conformable to at μ=1.5. By application the parameters alter theoptimized wavelet transform which is best suitable for denoising using Coif5 with soft threshold technique performs better solution to reconstruct the EEG signal.

- **Signal to Noise Ratio**

The signal to noise ratio is the ratio of the true signal amplitude to the standard deviation of the noise.The quality of the signal is termed as the signal-to-noise ratio, which is expressed as:

$$SNR = 10\log\frac{S_{original}}{S_{noise}}$$

Where, $S_{original}$represents the original signal without noise and S_{noise}represents the noisy signal.

- **Mean Square Error**

The difference between the denoisied signal and the original signal is given by the following equation:

$$MSE = \frac{1}{M}\sum_{j=1}^{M}(y(j) - \overline{y(j)})^2$$

Where, *y(j)* represents the original signal, *y(j')* represents the denoised signal and M represents thelength of the signal.

V. RESULTS

The results are shown in both graphical and tabulated forms for simulated EEG. Graphical results are shown in Figure 5 and Figure 9 (**X-axis for No of samples and Y-axis for amplitude in µV**). In table 1 have results of FFT based wavelet denosing EEG signals contains Singal-to-Noise Ratio and Computation Time for DWT-Haar, DWT-DB5 and DWT-Coif5 real EEG and Table 2& Table 4 have results of simulated EEG data. In table 2 have the results of wavelet hard and soft threshold denoising techniques applied to obtain the Signal-to-Noise Ration, Root Mean Square Error and computation time.

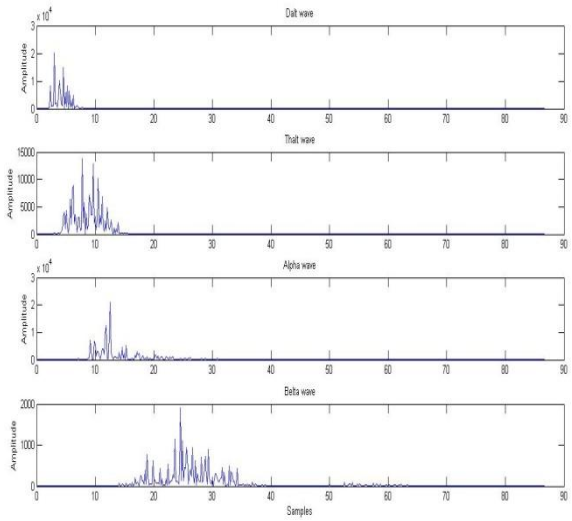

Figure 4 DWT-FFT Output Waveform

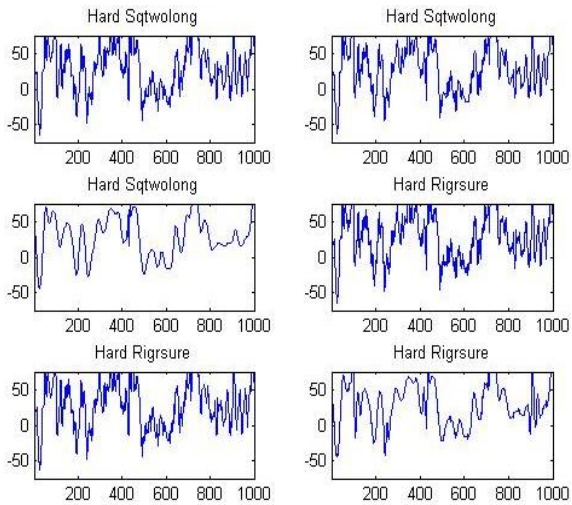

Figure 5 DWT Hard Fixed & Adaptive threshold

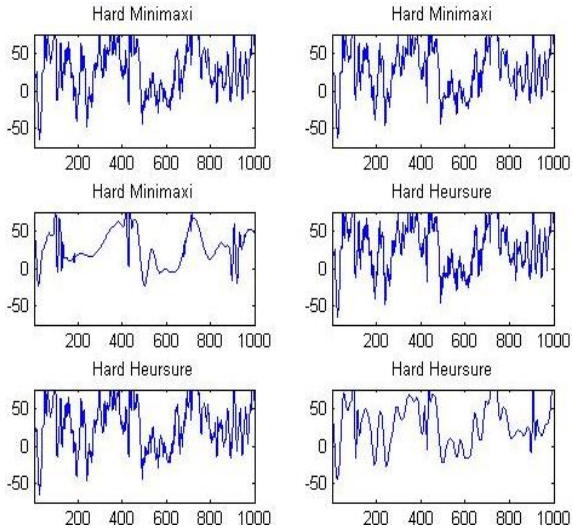

Figure 6 DWT Hard Minimax and Heuristic variant

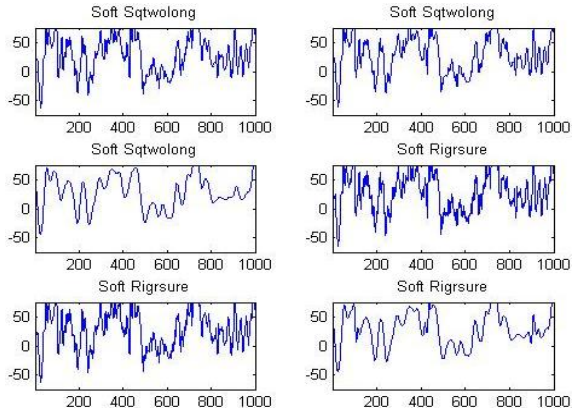

Figure 7 DWT Soft Fixed & Adaptive threshold variant threshold

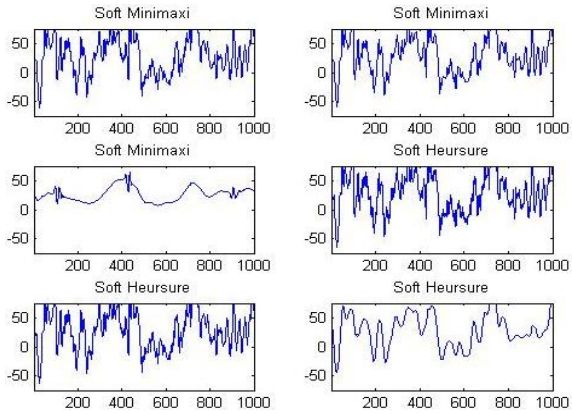

Figure 8 DWT Soft Minimax and Heuristic

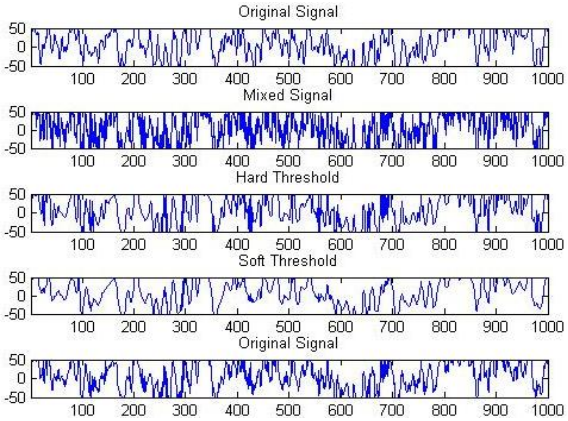

Figure 9Wave Threshold Output Waveform

VI. CONCLUSION

Outlander the deserts, it is practical to turn this way the so so rage in denoising of EEG warn, talent by EMG echo, is lose concentration the best-denoised caution is rival to DT(DB5)-DWT followed by DD-DWT, DT-DWT, and DWT. Way the best outgrowth is proportionate to Delicate Thresholding followed by Weak Thresholding relative to μ = 1.5. Changeless Thresholding and Neighboring Coefficients Thresholding are competing for all over a couple of possibilities and in different cases pair gives emendate miserly than the adjustment and vice-versa but both are illustrious unskillful niggardly as compared to soft Thresholding.

The on rage follows for both the RealTime EEG details as richly as for the simulated EEG information, this shows the tangible exposition meander the practical observation are unmixed for the EMG resound. For both the Real-Time EEG facts and the Worked EEG data the best result is corresponding to decomposition using DWT with Soft Thresholding. In this case, the percentage denoising for Real-Time EEG data is 97.3963% respectively.

REFERENCES

1. Rangaraj M. Rangayyan, “Biomedical Signal Analysis A Case study Approach”, IEEE Press, 2005.
2. Stephane Mallat, “A Wavelet Tour of signal Processing”, Elsevier, 2006.
3. A. Tiwari and P. Khatwani “A survey on different noise removal techniques of EEG signals,” IJARRCE, vol- 2, Issue 2, February- 2013, pp. 1091-1095.
4. G.Inuso,” Wavelet-ICA methodology for efficient artifact removal from Electroencephalographic recordings,” Proceedings of International Joint Conference on Neural-Networks, Orlando (Florida)-USA, 12-17 August- 2007.
5. J. Gao, H. Sultan, J. Hu and W. W. Tung, “Denoising nonlinear time series by adaptive filtering and wavelet shrinkage: a comparison,” IEEE Signal Processing Letter vol-17, No-3, 2010, pp. 237-240.
6. A.D Cheveigné, and J Z Simon, "De-noising based on time shift PCA," J Neurosci Met, vol-165, no. 2, 2007, pp. 297-305.
7. H Leung, K Schindler, A Y Chan, A Y Lau and K L Leung “Wavelet de-noising of electroencephalogram and the absolute slope method: A new tool to improve electroencephalographic localization and lateralization,” ClinNeurophysiol, vol-120, No-7, 2009, pp. 1273-1281.
8. S S Patil and M K Pawar, “Quality advancement of EEG by wavelet-denoising for biomedical analysis,” ICCICT, 2012, pp. 1-6.
9. L Leung, E H Ng and K S Wong, “Wavelet-denoising of electroencephalogram and the absolute slope method: A new tool to improve electroencephalographic localization and lateralization,” ClinNeurophysiol, vol.120, no. 7, 2009,pp. 1273-1281.
10. K Asaduzzaman, M B I Reaz, F Mohd Yasin, K S Sim and M S Hussain, “A study on discrete wavelet basednoise removal from EEG signals,” In advances in computational biology, Springer, 2010, pp. 593-599.
11. X Yong, R K Ward and G E Birch, “Artifact removal in EEG using morphological component analysis,” Department of Electrical and Computer Engineering, University of British Columbia, PP 345-348.
12. S. Lal, M. Chandra, G.K. Upadhayay and D Gupta” Removal of Additive Gaussian Noise by Complex Double Density Dual Tree Discrete Wavelet Transform” MIT, IJ ECE, Vol-1, pp. 8-16, Jan- 2011.
13. T. He, et al., "Application of independent component analysis in removing artefacts fromthe electrocardiogram," Neural Computing & Applications, vol. 15, pp. 105-116,2006
14. A.D Cheveigné, and J Z Simon, "De-noising based ontime shift PCA," J Neurosci Met, vol-165, no. 2, 2007,pp. 297-305.
15. [15] Md. Ashfanoor Kabir and Celia Shahnaz, “Comparison of ECG signal Denoising Algorithms in EMD andWavelet Domains”, vol1 Issue3, 2012.
16. Hilton de O. Mota and Flavio H. Vasconcelos, “Data processing system for denoising of signals in realtime using the wavelet transform” Third International Workshop on Intelligent Solutions in Embedded Systems, 2005., IEEE Xplore, 10.1109/WISES.2005.1438721
17. S. Lal, M. Chandra, G.K. Upadhayay and D Gupta” Removal of Additive Gaussian Noiseby ComplexDouble Density Dual Tree Discrete Wavelet Transform” MIT, IJ ECE, Vol-1, pp. 8-16, Jan- 2011.
18. R Gomathi& S Selvakumaran, “A Bi-variate Shrinkage Function For Complex Dual Tree DWT Based Image Denoising ,” In Proc. ICWAMS-2006, Bucharest- Romania, 16-18 October- 2006.
19. L Sendur and I W Selesnick, “Bi-variate shrinkage with local variance estimation,” IEEE Sig Proc Letters,9(12), December- 2002.
20. L Sendur and I W Selesnick, “Bi-variate shrinkage functions for wavelet based de-noising exploitinginterscale dependency,” IEEE Tran on Sig Proc, 50(11):2744-2756, November -2002.
21. E.-S. El-Dahshan, "Genetic algorithm and wavelet hybrid scheme for ECG signal denoising," Telecommunication Systems, vol. 46, pp. 209-215, 2010.
22. C.K.S Vijila and C.E.S Kumar, “Interference Cancellation in EMG signal UsingANFIS”, International Journal of Recent Trends in Engineering, Vol.2, pp. 244-248, 2009.
23. M Johnstone, B W Silverman, "Wavelet thresholdestimators for data with correlated noise", J R Statist.Soc Ser. B vol-59, 1997, pp.319–351.
24. Donoho and D L “De-noising by soft thresholding”. IEEE Transaction on Inform Theory-41, 613-627 (1995).