Neuro-Wavelet Techniques for GSI Denoising

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Abstract

This paper describes a new method of removing additive white noise of known variance from photographic images. This method is based on a characterization of statistical properties of natural images represented in complex wavelet decomposition. Specifically, we decompose the noisy image into wavelet subbands, denoising the subbands using wavelet. The proposed method is more efficient compared to use the wavelet techniques only. In this paper six methods are used to estimate the threshold value.

Keyword: WN (Wavelet Network), GSI (Gray Scale Image), DWT (Discrete Wavelet Transform), LOD (Level of Decomposition), NN (Neural Network).

1. Introduction

Through developing the technologies of transmission media, most of data and information was transmitted using these technologies, but during transmission the data is corrupted by many types of noise such as zero mean white Gaussian noise with specific standard deviation and at the receiving point, the noisy data such as image in this paper required extracting the pure image from noisy image, and this process is called denoising.

The following steps represent the mechanization of the proposed method:

Step1: Input a noisy image.
Step2: Use neuro-wavelet techniques to approximate the noisy image.
Step3: Apply wavelet multi-level of decomposition (LOD) to the approximated noisy image.
Step4: Is optimal LOD is reached if not return to step3.
Step5: Denoising subband of the approximated noisy image using soft or hard thresholding.
Step6: Recover the denoised image by applying inverse discrete wavelet transform (IDWT).

2. Objective of the Work

Wavelets, as a mathematical tool, have received extensive attention in the engineering profession during the last two decades. From mid 1980's till now, wavelet techniques have been implemented in many applications such as: image processing, medical diagnostics, geophysical signal processing, pattern recognition. But wavelet always limited to wavelets of small dimension. It is also well known that the neural networks (NNs) are powerful for handling problems of large dimensions, but their implementations suffer from the lack of efficient constructive methods, such as determining the network structure and falling into local minimum. Integrating wavelets and (NNs) can hopefully remedy the weakness of each other, resulting in networks with efficient constructive methods and capable of handling problems of moderately large dimension [1].

3. Neuro-Wavelet Techniques for Approximating the Noisy Image

Wavelet network have been established as a general and powerful approximation tool for filtering the noisy image.

This combined technique uses special mother wavelet $\Psi_{a,b}$ as activation function for NNs instead of the traditional activation function. The wavenet structure shown in figure (1) approximates any desired signal y by generalizing a linear combination of a set of daughter wavelets, where the daughter wavelets are generated by dilation *a*, and translation *b*, from a mother wavelet.

The chose of mother wavelet depends on the type of signal. The signal here represents function of two variables (images), then it will require two variable mother functions:

$$\Psi_{a,b}(t_1,t_2)=\Psi(\frac{t_1-b}{a},\frac{t_2-b}{a})$$

where:

a: Dilation factor ($a>0$).

b: Translation factor.

The approximated signal of the network y can be represented by:

$$y=u\times\sum_{k=1}^{k}w_k\Psi_{a_k,b_k}$$

where *k* is a number of windowing wavelets, and w_k is the weight coefficients, y,u, and $\Psi_{a,b}$ may be one single variable or multivariable depend on input function [2].

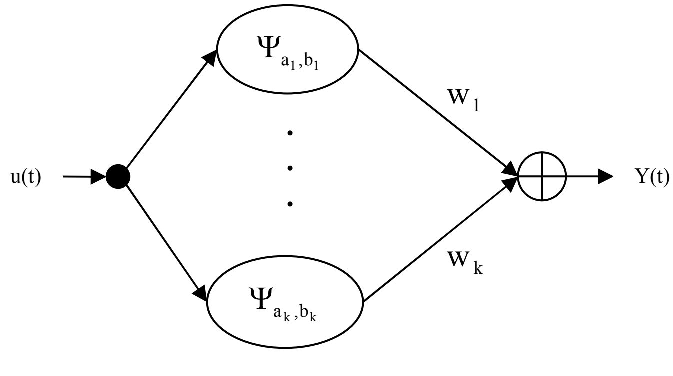


Figure (1): Adaptive Wavenet Structure.

The wavenet parameters w_k,a_k,b_k in multivariable functions can be optimized in the least mean square (LMS) algorithm by minimizing a cost function or the energy function, over all dimension of function. Thus by denoting:

$$e(i,j)=u(i,j)-g(i,j)$$

so, the energy function is defined by:

$$E=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}e^2(i,j)$$

$$E=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(u(i,j)-g(i,j))^2$$

where:

M, N = Dimensions of the function.

To minimize E we may use the method of steepest descent, which requires the gradients $\frac{\partial E}{\partial w_k},\frac{\partial E}{\partial a_k},\frac{\partial E}{\partial b_k}$ for updating the incremental changes to each particular parameter w_k,a_k,b_k respectively. The gradients of E are:

$$\frac{\partial E}{\partial w_k}=-\frac{2}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}e(i,j)g(i,j)\Psi_k(\tau_1,\tau_2)$$

$$\frac{\partial E}{\partial b_k}=-\frac{2}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}e(i,j)g(i,j)w_k\frac{\partial\Psi_k(\tau_1,\tau_2)}{\partial b_k}$$

$$\frac{\partial E}{\partial a_k}=-\frac{2}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}e(i,j)g(i,j)w_k\frac{\partial\Psi_k(\tau_1,\tau_2)}{\partial a_k}$$

where:

$$\tau_1=\frac{i-b_k}{a_k},\quad\tau_2=\frac{j-b_k}{a_k}$$

and the incremental changes of each coefficient are simply the negative of their gradients:

$$\Delta w=-\frac{\partial E}{\partial w},\ \Delta b=-\frac{\partial E}{\partial b},\ \Delta a=-\frac{\partial E}{\partial a}$$

Thus each coefficient of the network (w, a, b) are updated according to:

$$w(n+1)=w(n)+\mu_w\Delta w$$

$$n+1)=b(n)+\mu_b\Delta b$$

$$a(n+1)=a(n)+\mu_a\Delta a$$

where μ is the fixed learning rate parameter between (10 and 100).

4- Applying Multi-Wavelet Level of Decomposition (LOD).

Since we use the input signal (image) which is a two dimensional (2-D), it is necessary to represent the signal components by 2-D wavelets and a 2–D approximation function. For any scaling function Φ with its coressponding wavelet Ψ, we construct three different 2-D wavelet and one 2-D approximation function. Corresponding to the scaling function Φ and the wavelet Ψ in one dimension are three 2-D wavelets and one 2-D scaling function at each level of resolution.

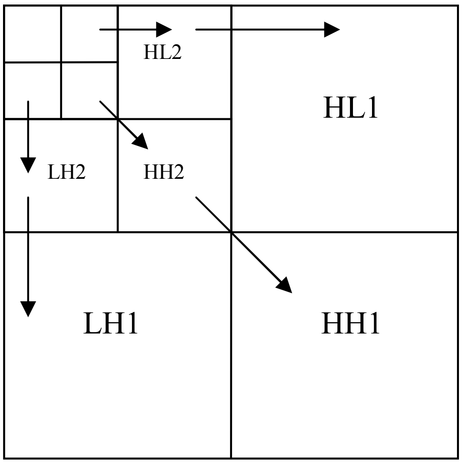
After applying wavelet decomposition using the scaling and wavelet functions we can get one approximated band and three detail bands as shown in figure (2) as explained in the following equations [3]:

$$LH=D^s{}_{m,k}=\left\langle f(x,g),\Phi^s{}_m(x)\Psi^s{}_k(g)\right\rangle$$

$$HL=D^s{}_{m,k}=\left\langle f(x,g),\Psi^s{}_m(x)\Phi^s{}_k(g)\right\rangle$$

$$HH=D^s{}_{m,k}=\left\langle f(x,g),\Psi^s{}_m(x)\Psi^s{}_k(g)\right\rangle$$

$$LL=C^s{}_{m,k}=\left\langle f(x,g),\Phi^s{}_m(x)\Phi^s{}_k(g)\right\rangle$$



Figure(2): 2-D 3-scale DWT.

5- De-noising using threshold techniques

Thresholding is nonlinear operation that will be performed on all subbands of wavelet coefficients except the lowpass residual band of the noisy signal. To avoid shortcoming of the linear filtering often a nonlinear procedure is used to suppress the noise in the empirical wavelet coefficients [4].

Therefore, one could estimate the empirical wavelet coefficients independently. To do this let's as compare the absolute value of the empirical wavelet coefficient with a value called Threshold Value (*Tv*) where six rules discussed in this paper to select this threshold value in general forms.

Generally, thresholding process has two types as will be given below.

1- Hard-thresholding

Hard thresholding also called (kill/keep) strategy, which is the simplest method, and can be stated mathematically as [5]:

$$\hat{C} = Th(C, Tv) = \begin{cases} C & |C| > Tv \\ 0 & |C| \le Tv \end{cases}$$

2- Soft-thresholding

Soft threshold is an alternative scheme of hard thresholding and can be stated as [5, 6]:

$$\hat{C} = Th(C, Tv) = \begin{cases} sign(c) \times (|C| - Tv) & |C| > Tv \\ 0 & |C| \le Tv \end{cases}$$

Where

$$sign(c) = \begin{cases} +1 \ \ if \ \ C > 0 \\ 0 \ \ if \ \ C = 0 \\ -1 \ \ if \ \ C < 0 \end{cases}$$

5.1 Selection of the threshold value (*Tv*)

In thresholding process, coefficients smaller than *Tv* are judged negligible, or noise other than signal. Hence, *Tv* controls the degree of noise rejection, in this paper six methods are used to select the value of *Tv*.

First method: One possibility of selecting the threshold is to select the threshold value by estimating the standard deviation σ_x of the noise at each coefficient, and taking into account that the threshold values have to different on each coefficient. The threshold in this case can be calculated as [6, 7]:

$$Tv = \frac{\sigma^2}{\sigma_x}$$

Where:

σ^2 : Represented noise power for noisy image (contaminated with Gaussian noise).

σ_x : Standard deviation for the detail coefficients as (Horizontal Detail (HL), Vertical Detail (LH), and Diagonal Detail (HH)) can be calculated by using the following equation:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{N-1} \sum_{j=1}^{M-1} (C_{ij} - m)^2}{M \times N}}$$

Noise power (σ^2) can be estimated by using Median Absolute Deviation:

$$\sigma = \frac{Median\left(|C_{ij}|\right)}{0.6745}$$

Second method: The threshold values in this case are calculated as [7]:

$$Tv = \frac{\sqrt{2\sigma_x^{\ 2} \ln N}}{2}$$

Where:

N: Dimension of each coefficient in detail band.

Third method: selection using principle of stein's unbiased risk estimate (SURE) (MatLab code "rigrsure") [8].

Fourth method: selection using fixed form threshold (MatLab code "sqtwolog") [8].
Fifth method: selection using a mixture of the third and fourth selection rules (MatLab code "heursure") [8].
Sixth Method: Selection using minimax principle (MatLab code "minimaxi") [8].

6. De-noising Subbands of the image using soft and hard thresholding [9].

The de-noising algorithm performs on the noisy subbands images without any rejection of any subbands and also applied with the rejection of the one or more subbands of the noisy image.

1. De-noising without rejection

This method used only soft or hard thresholding on the detail coefficients only without rejected any band in the detail-coefficients.

2. De-noising with rejection.

This method is divided into two ways:

a- The first way used thresholding and rejected one band from the first level of decomposition.
b- The second way used thresholding but rejected all details-coefficients from the first level of decomposition.

In this paper there are two approaches to de-noising the images, the first approach is based on eliminating the noisy bands and use the other band to reconstruct the image and the second approach is based on de-noising the subbands of the image and reconstruct the image and this approach is depend on the appropriate threshold value estimated using one of the previous six methods to estimate the threshold value.

7. Algorithm Evaluation

The proposed algorithm was performed on an image contaminated with Gaussian type noise with variance = 0.18, the MSE, PSNR before denoising are 76.1049, 17.17db respectively.

The neuro-wavelet algorithm used to approximate the noisy image, the wavelet network was initialized by the following parameters:

- Number of wavlons = 2;
- Dilation = 2;
- Cost function = 0.01;
- Learning rate of (weights, translations, and dilations) = 99;

The initial and final parameters are shown in table (1). where the initial parameters of wavelet network are chosen randomly (dilation, number of wavelons, and the learning rates for wavelet network parameters). The learning rate parameters for weights, dilations, and translations are all fixed at 0.01. a batch-mode learning of 13 sample data is adapted until the desired error of 0.01 is reached. Wavelet network has 10 wavelons. Total number of iterations needed was 3323.

The approximated image is shown in figure (3-c), with the approximated image is decomposed using wavelet transform into 3-levels.

Table (2), shows the performance obtained from de-noising by hard thresholding.

The perfect-denoised images with hard thresholding in both with and without rejection are shown in figure (3), and the curves of denoising using different filters by hard thresholding are shown in figure (5). table (3) represents the results of denoising by soft thresholding. While figure (4) shows the perfect denoised images using soft thrsholding with and without rejection, and figures (6) show, the relation between the MSE and the filter types using soft thresholding.

8. Conclusions and Future Work

The following points summarize the main conclusions and future work of this paper:

1- The neuro-wavelet techniques reduce the amount of noise in images and increase the brightness of the blind image. But also have some drawbacks where the cost function must be small and enough which may increase the number of iterations to arrive this value, and we must avoid falling in local minimum.
2- Increasing the numbers of LOD will increase the de-noising efficiency but for specified LOD.

3- Soft thresholding provide better results from hard thresholding in de-noising the noisy images.
4- The first method of choicing thresholding value is better than other five methods.
5- The de-noising with rejection of HH, HL, and LH bands for first level gave better results, also the rejection of HH band for the first level gave better results in case of low noise images.
6- Use another image sets with different sizes and different types of noise.
7- Apply other methods for selecting the thresholding value such as Genetic algorithm.
8- Try to use multi-wavelet decomposition as denoising algorithm.

9. References

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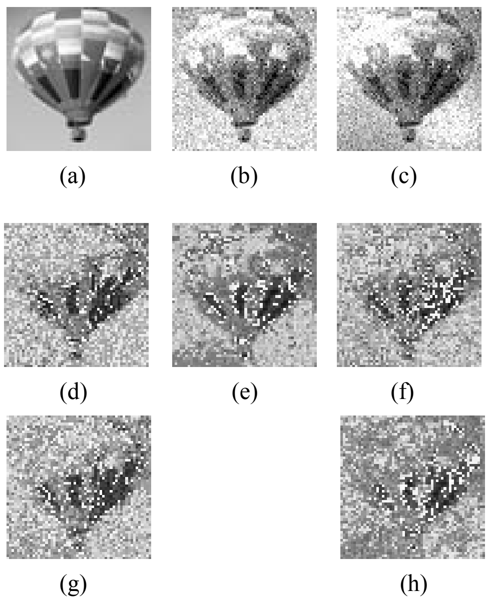


Figure (3) Perfect-denoised image a) Original pure image. b) Original image contaminated with variance=0.18 type Gaussian. c) Approximated noisy image. d) Denoising without rejection. e) Denoising with rejection HH1,HL1,LH1 band. f) Denoising with rejection HH1 band. g) Denoising with rejection HL1 band. h) Denoising with rejection LH1 band.

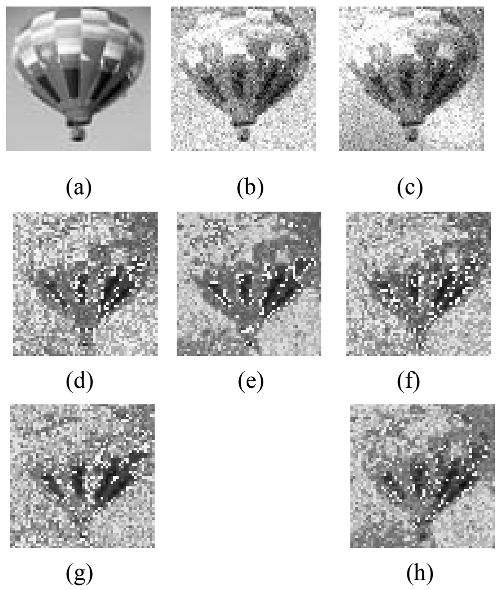
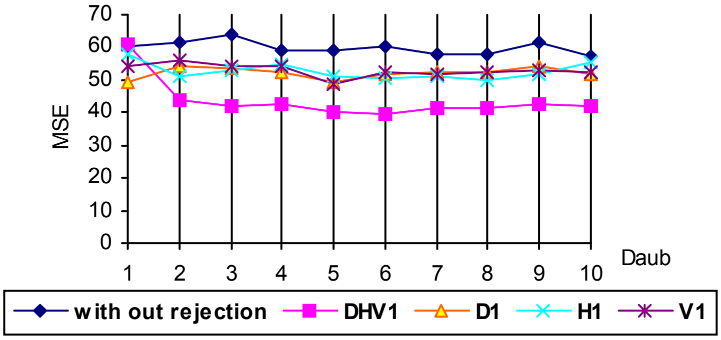
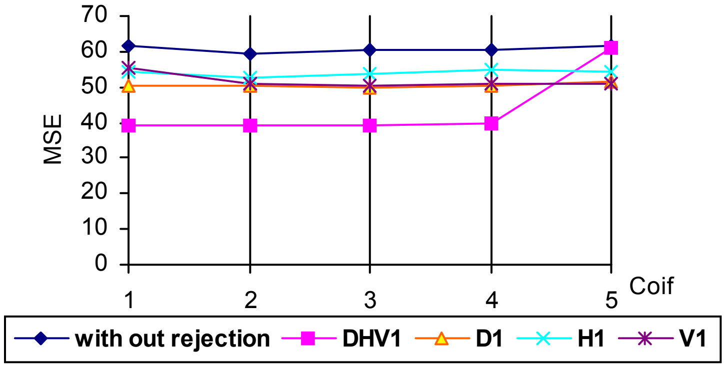


Figure (4) Perfect-denoised image a) Original pure image. b) Original image contaminated with variance=0.18 type Gaussian. c) Approximated noisy image. d) Denoising without rejection. e) Denoising with rejection HH1,HL1,LH1 band. f) Denoising with rejection HH1 band. g) Denoising with rejection HL1 band. h) Denoising with rejection LH1 band.



(a)



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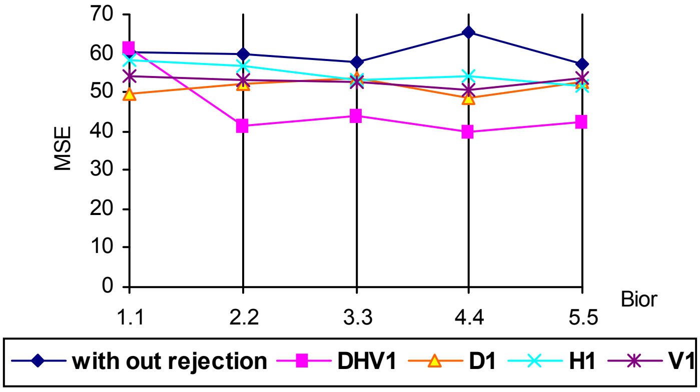
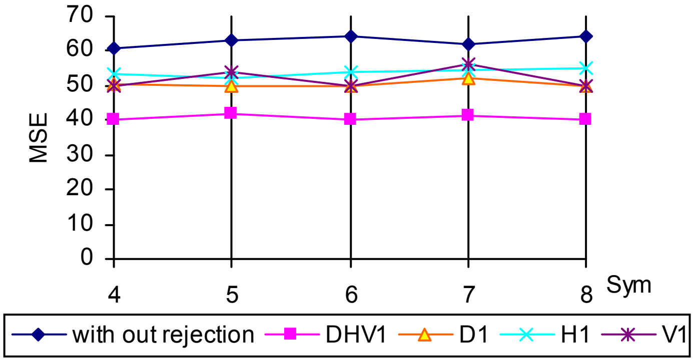
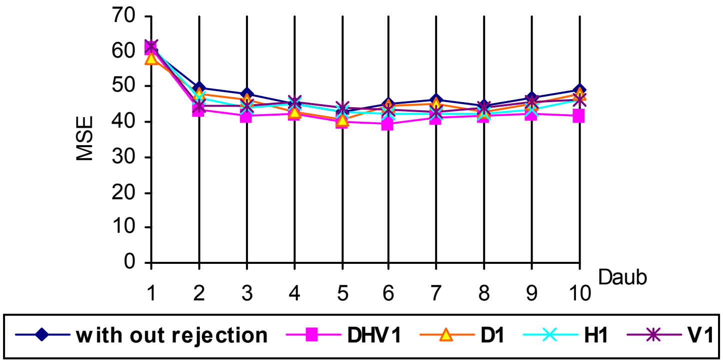


(c)

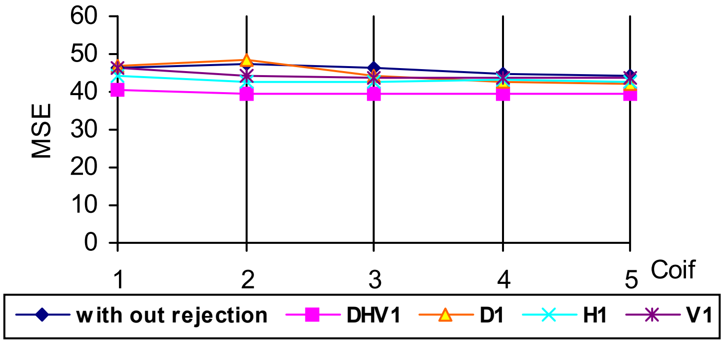


(d)

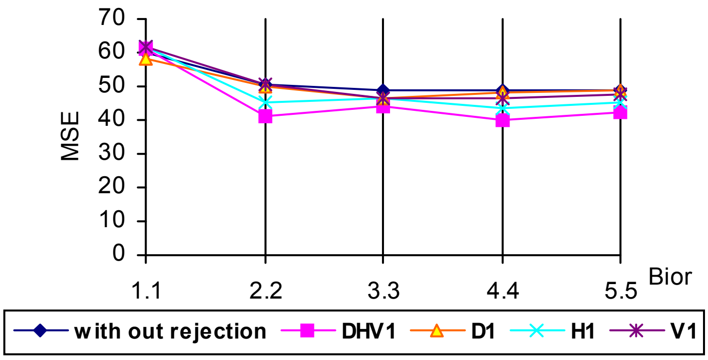
Figure (5) Curve of denoising algorithm, a) Daub filters, b) Coif filters, c) Bior filters, d) Sym filters



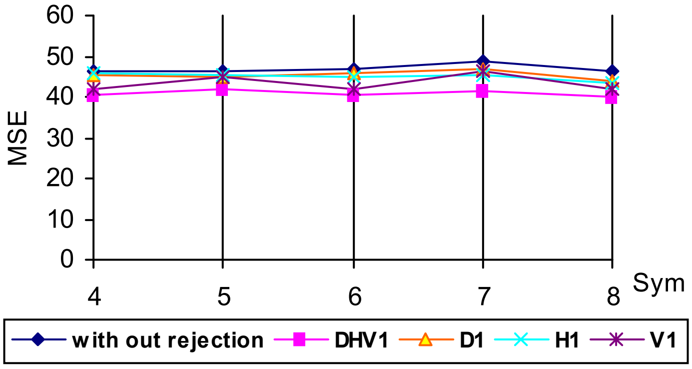
(a)



(b)



(c)



(d)

Figure (6) Curve of denoising algorithm, a) Daub filters, b) Coif filters, c) Bior filters, d) Sym filter.

Table (1): initial and final parameters of wavelet network

Initial parameters			Final parameters		
w	*a*	*b*	*w*	*a*	*b*
0	2	0	2.0017109	1.4685122	-0.395791
0	2	1.333334	1.9233605	2.7550271	0.4284082
0	2	2.666666	1.5402775	3.2319413	1.6757703
0	2	4	0.9685823	3.2845641	3.3349625
0	2	5.333333	0.6262195	2.0407144	4.9063841
0	2	6.6666666	0.4852279	1.7174964	5.9844387
0	2	8	0.6986117	1.8899168	8.0862862
0	2	9.3333333	1.1925555	3.2116096	9.3774172
0	2	10.6666666	0.2469432	2.5006195	11.219462
0	2	12	0.1932538	1.9301809	12.634066

Table (2): Result of hard thresholding.

filter	Denoising with out Rejection		Denoising with Rejection for first level							
			All Details bands		HH		HL		LH	
	MSE	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*
Db1	60.4815	18.1706	61.1488	18.1229	49.5051	19.0403	58.0403	18.3370	54.3145	18.6377
Db2	61.2512	18.1157	43.5876	19.5932	54.4751	18.6248	51.1439	18.8989	55.7973	18.5207
Db3	64.0563	17.9212	41.7218	19.7832	53.5111	18.7024	52.9531	18.7479	53.9222	18.6691
Db4	58.9152	18.2845	42.5788	19.6949	52.3690	18.7961	54.5360	18.6200	54.3775	18.6326
Db5	58.9070	18.2851	39.9933	19.9669	49.5056	19.0403	51.2987	18.8857	48.7143	19.1102
Db6	60.2812	18.1850	39.3633	20.0359	51.8361	18.8405	50.4505	18.9574	52.5178	18.7837
Db7	58.0378	18.3497	41.1421	19.8439	52.5347	18.7824	51.0501	18.9068	51.9117	18.8342
Db8	57.6377	18.3797	41.5355	19.8026	52.4736	18.7874	49.9204	19.0040	52.5604	18.7802
Db9	61.5557	18.0941	42.5278	19.7001	54.1265	18.6527	51.8098	18.8427	53.0373	18.7410
Db10	57.3001	18.4053	41.7330	19.7820	51.6277	18.8580	55.3488	18.5557	52.5455	18.7815
Coif1	61.5822	18.0923	40.4402	19.9187	50.4340	18.9595	54.2771	18.6406	55.6557	18.5317
Coif2	59.1992	18.2637	39.2358	20.0500	50.3430	18.9674	52.7408	18.7653	50.9009	18.9196
Coif3	60.5053	18.1689	39.2652	20.0467	50.1173	18.9869	53.6761	18.6890	50.5801	18.9470
Coif4	60.4017	18.1763	39.4613	20.0251	50.4507	18.9581	54.8045	18.5987	50.8575	18.9233
Coif5	61.5773	18.0926	39.7077	19.9981	51.4848	18.8700	54.1265	18.6527	50.8256	18.9260
Bior1.1	60.4815	18.1706	61.1488	18.1229	49.5051	19.0403	58.2084	18.3370	54.3145	18.6377
Bior2.2	59.6395	18.2315	41.3198	19.8252	52.3058	18.8013	56.6530	18.4546	52.9965	18.7443
Bior3.3	57.9780	18.3542	43.9846	19.5538	53.8580	18.6743	53.3744	18.7135	52.5527	18.7809
Bior4.4	65.6337	17.8155	39.7296	19.9957	48.7878	19.1037	53.9305	18.6685	50.6530	18.9408
Bior5.5	57.0856	18.4215	42.3858	19.7146	52.7227	18.7668	51.5612	18.8636	53.7060	18.6866
Sym4	60.9297	18.1385	40.4457	19.9181	50.6270	18.9430	53.3825	18.7128	49.8526	19.0099
Sym5	63.2729	17.9746	42.0744	19.7466	49.6714	19.0258	52.4368	18.7905	53.7551	18.6826
Sym6	64.3199	17.9034	40.3747	19.9257	49.8975	19.0060	53.8742	18.6730	49.9025	19.0056
Sym7	61.8750	18.0717	41.3514	19.8219	52.4481	18.7895	54.2502	18.6428	56.2715	18.4839
Sym8	64.5343	17.8889	40.2207	19.9423	50.0574	18.9921	55.1513	18.5713	49.9703	18.9997

Table (3): Result of soft thresholding.

filter	Denoising with out Rejection		Denoising with Rejection for first level							
			All Details bands		HH		HL		LH	
	MSE	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*	*MSE*	*PSNR*
Db1	60.2307	18.1886	60.9707	18.1356	58.2594	18.3332	61.7270	18.0821	61.6094	18.0903
Db2	49.9588	19.0007	43.5916	19.5928	47.8775	19.1855	46.8394	19.2807	44.8304	19.4711
Db3	47.7814	19.1942	41.7200	19.7834	46.1824	19.3420	44.0718	19.5452	44.4062	19.5124
Db4	45.0593	19.4490	42.5499	19.6948	43.0444	19.6476	45.1380	19.4414	45.7229	19.3855
Db5	42.9192	19.6603	39.9938	19.9669	40.3635	19.9269	42.7442	19.6780	43.9774	19.5545
Db6	45.3678	19.4193	39.3632	20.0359	44.4505	19.5080	42.5844	19.6943	43.5515	19.5968
Db7	46.1607	19.3441	41.1421	19.8439	44.9247	19.4620	42.4529	19.7077	43.0429	19.6478
Db8	44.4929	19.5039	41.5355	19.8026	43.0929	19.6428	42.5123	19.7017	43.8219	19.5699
Db9	47.1351	19.2534	42.5277	19.7001	45.2021	19.4352	43.6465	19.5873	45.5245	19.4044
Db10	49.1189	19.0743	41.7330	19.7820	47.7530	19.1968	46.1425	19.3458	46.2115	19.3393
Coif1	46.0975	19.3500	40.4395	19.9188	46.7494	19.2891	44.3110	19.5217	46.5217	19.2846
Coif2	47.4622	19.2233	39.2357	20.0500	48.3813	19.1400	42.5841	19.6943	44.3139	19.5214
Coif3	46.0638	19.3532	39.2652	20.0467	44.3214	19.5207	42.6925	19.6833	43.8072	19.5714
Coif4	44.5512	19.4982	39.4613	20.0251	42.7675	19.6757	43.0201	19.6501	43.6847	19.5835
Coif5	44.0632	19.5461	39.7077	19.9981	42.2012	19.7336	42.6938	19.6832	43.4653	19.6054
Bior1.1	60.2307	18.1886	60.9707	18.1356	58.2594	18.3332	61.7270	18.0821	61.6094	18.0903
Bior2.2	50.5025	18.9537	41.3198	19.8252	50.0419	18.9935	45.0347	19.4513	50.3527	18.9666
Bior3.3	48.5617	19.1239	43.9846	19.5538	46.6373	19.2995	46.7442	19.2895	46.6717	19.2963
Bior4.4	48.5449	19.1254	39.7296	19.9957	47.9726	19.1769	43.3219	19.6197	46.6526	19.2981
Bior5.5	48.7174	19.1100	42.3868	19.7145	48.7145	19.1494	45.4085	19.4154	47.6357	19.2075
Sym4	46.5113	19.3112	40.4464	19.9180	45.5499	19.4019	45.7486	19.3830	42.1029	19.7473
Sym5	46.2257	19.3380	42.0734	19.7467	44.6948	19.4842	45.2334	19.4322	44.6427	19.5069
Sym6	46.7511	19.2889	40.3753	19.9256	46.0302	19.3564	45.0513	19.4497	42.0708	19.7470
Sym7	48.8009	19.1025	41.3514	19.8219	46.6500	19.2983	45.3356	19.4224	46.5837	19.3045
Sym8	46.1759	19.3427	40.2206	19.9423	43.8446	19.5676	43.3678	19.6151	42.1520	19.7386