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Image Denoising using Discrete Wavelet Transform

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Abstract – Eliminating noise from the original signal is still a difficult assignment for researchers. There have been several available algorithms that aim to remove noise from original signal. This paper presents an algorithm for denoising image using wavelet transforms. The exercise of wavelet transforms improves the excellence of an image and reduces noise level. It works on Haar and Daubechies wavelet Transforms. The image is first decomposed , then the level of soft and hard threshold is selected for reducing the noise in the image and finally the image is reconstructed and by calculating the PSNR , MSE and BETA (Energy retained parameter) and entropy performance evaluation is done.

Keywords – Wavelet transform, Haar, Daubechies, Threshold, Entropy, Rigrsure.

I. INTRODUCTION

Image processing is a field that continues to grow with an ever increasing speed with application areas ranging from the entertainment industry to the space program. One of the most fascinating aspect of this information rebellion is the ability to send and receive complex data. Visual information, transmitted in the form of digital images, has turned out to be a major method of communication for the 21st century.

Images are often despoiled with noise during acquirement, broadcast, and retrieval from storage media or noise may be present due to some environmental conditions like rain, snow etc. Many dots can be patterned in a photograph taken with a digital camera under low illumination conditions. Fig.1 is an example of such a photograph. Appearance of dots is due to the original signals getting corrupted by unwanted signals. The principle of the denoising algorithm is to remove such noise from the experimental signal, and help the recovery of functions of that signal. Image denoising is desirable because a noisy image is not pleasant to view, bad for compression and bad for analysis. In addition, some fine details in the image may be puzzled with the noise or vice-versa. Many image-processing algorithms such as pattern recognition call for a clean image to work efficiently.

The problem of Image de-noising can be defined as follows:

Let A(i, j) be the noise-free image and B(i, j) be the image despoiled with noise Z(i, j) ,

$$B(i, j) = A(i, j) + Z(i, j) \qquad ...(1.1)$$

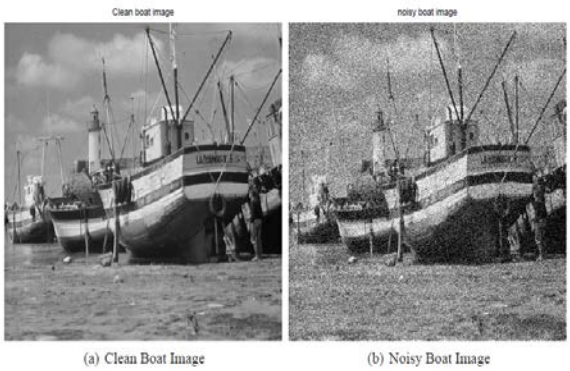

Fig.1. Illustration of noise in the image

The problem is to estimate the desired signal as precisely as possible according to some criterion.

In the wavelet domain, the problem can be formulated as:

$$Y(i, j) = W(i, j) + N(i, j) \qquad ...(1.2)$$

where Y(i, j) is noisy wavelet coefficient; W(i, j) is true coefficient and N(i, j) noise.

De-noising of images corrupted by noise using wavelet techniques is very effectual because of its ability to confine the energy of a signal in few energy transform values. There is no necessity to block the image. It is more robust under transmission errors. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the wavelet transform. The wavelet transform yields a large number of small coefficients and a small number of large coefficients. The wavelets give advanced performance due to:

- Property of Sparsity
- Multiresolution structure
- Multiscale nature

Introduction to wavelet families: The Haar, Daubechies, Symlets and Coiflets are various types of wavelets. These wavelets are competent of ideal reconstruction. We are using Haar and Daubechies wavelets in our algorithm.

Haar wavelet: Haar wavelet is one of the oldest and simplest type of wavelet. The Haar Transform provides sample for all other wavelet transforms. Like other wavelet transforms, the Haar Transform decomposes the discrete signal into two sub-signals of half of its length. One sub-signal is a successively average or trend and other sub-signal

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is successively difference or fluctuation. The advantage of Haar wavelet is that it is rapid, memory competent and conceptually simple.

Daubechies Wavelet: A family of wavelet transforms exposed by Ingrid Daubechies . The Concepts are very much similar to Haar but differs in how scaling functions and wavelets are defined . Daubechies wavelets are ready to lend a hand in compression and noise elimination of audio signal processing because of its property of overlapping windows and the high frequency coefficient spectrum that reflects all high frequency changes.

II. Material & Methods

We propose a hybrid method of image de-noising based on the combination of the wavelets and thresholding while denoising. Wavelet transforms can be used in tasks ranging from edge recognition to image smoothing because they provide significant insight into both an image's spatial and frequency characteristics, wavelets can also be used in applications in which Fourier methods are not compatible, like progressive image reconstruction.

We will use the wavelet noise thresholding which is Discrete Wavelet Transform (DWT). In the case of DWT first the image is alienated into the four parts HH, HL, LH, and LL and the further the approximation part i.e. LL is divided into two sub-bands. And the other part is detailed part in which we have all three parts HH, HL and LH as shown in fig.2.We will work on the detailed part because the noise will occur on the high frequency part i.e. the detailed part.

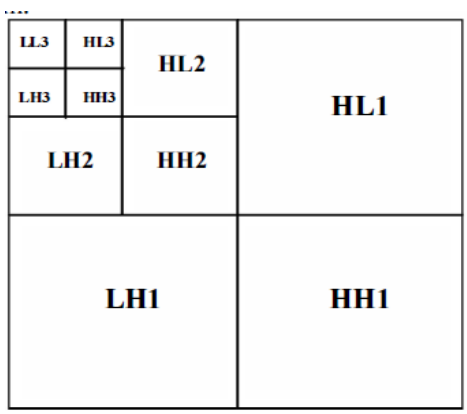

Fig. 2. Image Decomposition (3 Level) using DWT

DWT is used to diminish the noise from the image. It has three steps which are given below:

1. Compute the two-dimensional wavelet transform of an image.
2. Change the transform coefficients.
3. Calculate the inverse transform.

Two types of thresholding functions are there soft and hard thresholding. Soft thresholding reduces or deletes the high frequency components in which noise is present but it also loses some required information. Hard thresholding reduces or deletes the low frequency components which also lose the some necessary information. Further we are using two types of thresholding methods: Global and Adaptive for both hard and soft thresholding.

STEPS OF PROPOSED METHODOLOGY:

Step 1: Load the original image X of size N×N.

Step 2: Choose the type of wavelet used: Haar or Daubechies.

Step 3: Choose the level of decomposition of image.

Step 4: It involves the decomposition of image using wavelets at different levels. After decomposition, detailed and approximation coefficients are extracted at each level. Approximation coefficients are used at further level for decomposition while detailed coefficients are kept for use while reconstruction.

Step 5: Reconstruction has been carried out using thresholded detailed coefficients and approximation coefficients. We applied hard and soft thresholding both for global as well as adaptive. Below is the figure that describes outputs when hard and soft thresholding are applied on a signal.

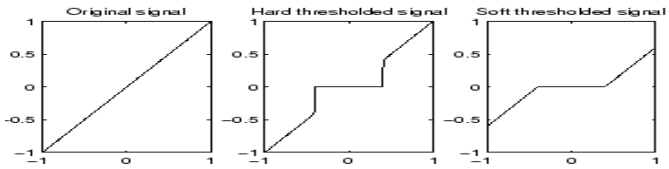

Fig.3: Orginal signal with hard and soft thresholding

The hard-thresholding function selects all wavelet coefficients that are greater than the given threshold λ and sets the others to zero. If the absolute value of a coefficient is less than a threshold, then it is assumed to be 0, otherwise it is unchanged. Mathematically it is

$$f_h(x) = x, \text{ if } x \geq \lambda$$
$$= 0, \text{ otherwise}$$

The soft-thresholding function has a different rule from the hard-thresholding function. It shrinks the wavelet coefficients by λ towards zero. If the absolute value of a coefficient is less than a threshold λ, then is assumed to be 0, otherwise its value is shrunk by λ. Mathematically it is

$$f(x) = x - \lambda, \text{ if } x \geq \lambda$$
$$= 0, \text{ if } x < \lambda$$
$$= x + \lambda, \text{ if } x \leq -\lambda$$

Step 6: It involves de-noising after applying rigrsure threshold to detailed coefficients. This step works as reconstructing the image by using approximation and detailed coefficients at corresponding level and we get the final denoised image.

Step 7: Finally calculate the performance measure parameters :

a) In statistics, the mean squared error of an estimated image is the difference between an estimated value of quantity and the true value of the quantity being estimated i.e. difference between the original image and the denoised image. Mean squared error (MSE) is calculated as follows: MSE = I, J [original(i, j) – de-noised(i, j)]2/ i*j

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b) PSNR is the peak signal to noise ratio, here signal is the original Image and noise is error introduced by restoration. PSNR is y used to measure the quality of reconstruction image with respect to the original image. A higher PSNR would normally indicate that the reconstruction is of higher quality. The PSNR which is defined in dB is calculated using formula: PSNR = 10log10 *(R^2/MSE)

c) Other parameter used for comparing the results is energy retained scores PERFL2 which can be computed as follows:

PERFL2 = 100 * (vector-norm of WP-cfs of XD / vector-norm of WP-cfs of X)2.

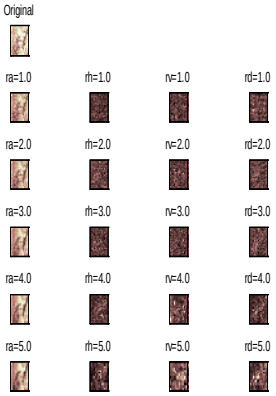
d) Entropy is defined as sum(p.*log2(p)) where p contains the histogram counts returned from IMHIST.ENTROPY uses 2 bins in IMHIST for logical arrays and 256 bins for uint8, double or uint16 arrays.

III. RESULTS & DISCUSSIONS

Experimental results of proposed scheme have been discussed in this portion in which we used one images of infected kidney and liver and one each of Lena, woman and Charlie. We also provided data for different images in the tables but resulted output at different points has been given away for only single image Lena. Corresponding MSE's, PSNR's and Energy retained parameters and entropy have been calculated and analysed further. Below are some image results from a to e after applying the proposed algorithm:

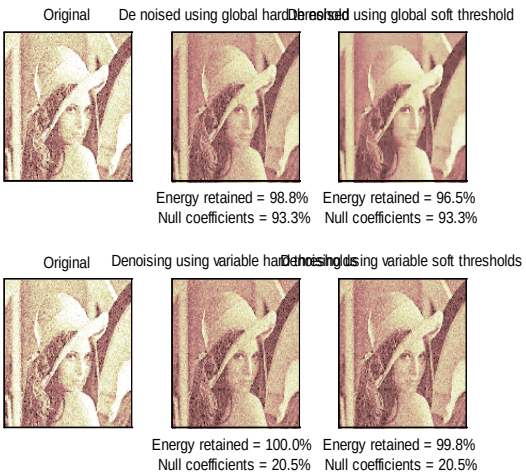
a) Original image

b) Three level decomposition in pyramid form



c) Three level decomposition in normal form

d) Reconstructed image



e) De-noised image at level 5

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Below is the tabular data for MSE, PSNR and energy retained parameter (BETA),ENTROPY by using Daubechies Wavelets at optimum threshold value 1:

Table 1: MSE values for images using DB4 at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	1.481	4.9411	139.9939	276.5168
Liver.jpg	0.1222	2.9592	320.9882	362.4401
Woman.jpg	0.1612	2.2148	168.9144	312.668
Charlie.jpg	2.3768	5.1848	92.4893	184.8242

Table 2:PSNR (in DB) values for images using DB4 at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	46.4253	41.1925	26.6697	23.7136
Liver.jpg	57.2617	43.4191	23.0659	22.5384
Woman.jpg	56.0581	44.6774	25.8541	23.18
Charlie.jpg	44.3708	40.9835	28.4699	25.4632

Table 3:BETA(in %) values for images using DB4 at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	99.5314	98.1095	99.9953	99.8583
Liver.jpg	93.5548	91.0749	99.9968	98.9794
Woman.jpg	99.6104	98.5601	99.9996	99.8959
Charlie.jpg	99.4602	97.6192	99.9866	99.7692

Table 4: Entropy values for images using DB4 at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	7.6188	7.4269	7.7017	7.6913
Liver.jpg	6.2200	6.2911	6.9441	7.0135
Woman.jpg	7.5765	7.3603	7.6230	7.612
Charlie.jpg	7.7938	7.6253	7.8050	7.815

As seen from the tables above Global hard and Global soft threshold gives improved results. If we compare both hard and soft threshold outputs, hard contains more information as it has high PSNR and BETA parameter but fails in noise reduction. On the other hand soft threshold provides better noise-reduction but has vanished some important spatial information due to low BETA factor. From above discussion, there is a negotiation on the selection of hard and soft threshold which depends upon the type of the application. As shown below in case of ultrasound image of liver one needs to reduce noise or need smoothness in order to observe the boundaries of the infected portions.

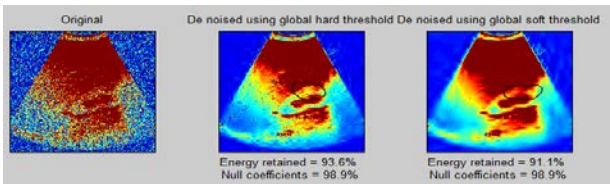

Fig. 4.: Noise reduction in order to enhance borders of different organs in liver image

Following are the graphs for MSE , PSNR and BETA (Energy retained parameter),ENTROPY ploted for DB4 at Level 5 by using the values given in Table 1,Table2, Table3,Table4 respectively.

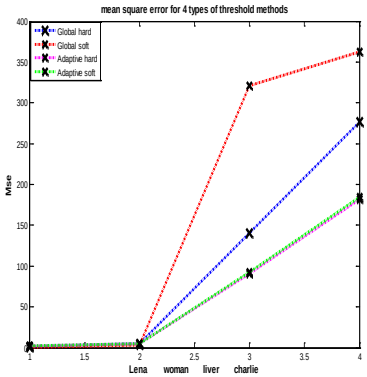

Fig.5:MSE value plots for images using DB4 at level 5

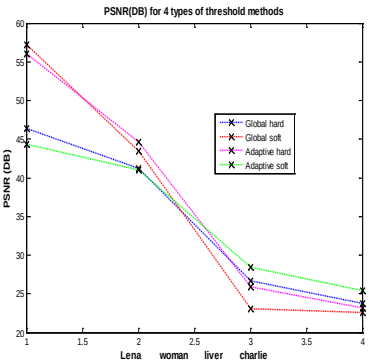

Fig. 6: PSNR value plots for images using DB4 at level 5

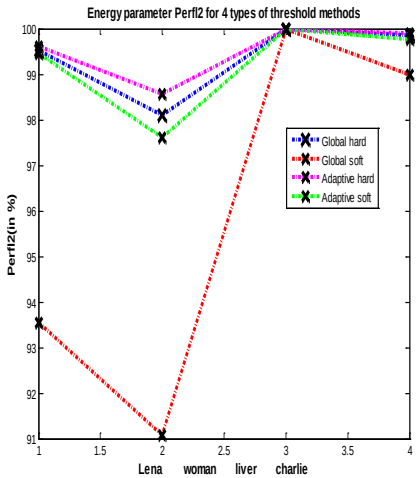

Fig. 7: BETA value plots for images using D B4 at level 5

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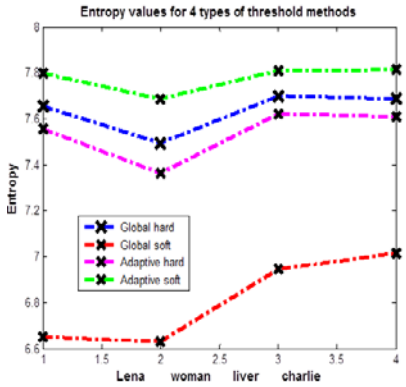

Fig. 8: Entropy value plots for images using DB4 at level 5

From above figures, we can see that Global threshold provide enhanced results in PSNR values and also have low MSE values. Adaptive hard and soft threshold have low PSNR values and very high MSE but have high BETA values. We are taking Entropy as performance measure which shows adaptive soft denoise the image with improved image quality by preserving the edges. If we compare all the parameters, Global hard performs finest and better denoise the image.

Following tables are some results for MSE , PSNR and BETA (Energy retained parameter),ENTROPY by using HAAR Wavelet at level 5 for four different test images at optimum threshold value 1:

Table 5: MSE values for images using HAAR at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	0.8792	3.6025	214.4953	357.8202
Liver.jpg	0.0801	2.3350	325.6393	373.0794
Woman.jpg	2.0212	2.9262	123.4367	279.7467
Charlie.jpg	2.0134	3.7445	94.5022	192.7228

Table 6: PSNR (DB) values for images using HAAR at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	48.6898	42.5647	24.8166	22.5941
Liver.jpg	59.0914	44.4479	23.0034	22.4127
Woman.jpg	45.0746	43.4677	27.2163	23.6631
Charlie.jpg	45.0913	42.3968	28.3763	25.2814

From Table 5 and 6, we can see that global hard and soft both have high PSNR values and low MSE. Adaptive hard and soft have comparatively low PSNR values. If we observe the beta factor from Table7, global soft has low BETA values .Global hard and Adaptive hard have high BETA values which means hard thresholding will denoise the image retaining edges. Now verify for entropy values from Table8, Adaptive soft have enhanced image texture after denoising. By considering all the factors we can say that Global Hard and Adaptive Hard performs best in denoising image without losing any details.

Table 7:BETA (%) values for images using HAAR at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	98.8194	96.5106	99.9952	99.7764
Liver.jpg	93.1784	90.4306	99.9983	99.0482
Woman.jpg	99.4793	97.3740	99.9915	99.8673
Charlie.jpg	99.3942	97.1657	99.9871	99.7609

Table 8: Entropy values for images using HAAR at level 5

Image	Global Hard	Global soft	Adaptive hard	Adaptive soft
Lena.jpg	7.654765	7.492544	7.699161	7.688424
Liver.jpg	6.650792	6.629063	6.947454	7.01369
Woman.jpg	7.557602	7.363204	7.621971	7.607651
Charlie.jpg	7.79752	7.685154	7.808738	7.814313

We can also plot the graphs of MSE, PSNR , BETA and ENTROPY after using HAAR Wavelet at level5 using the values of table 5, table 6, table 7, table 8 respectively as follows:

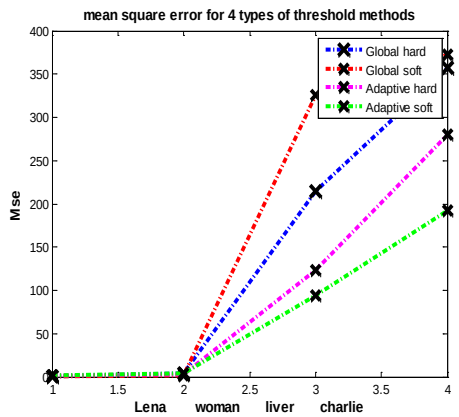

Fig. 9: MSE value plots for images using HAAR at level 5

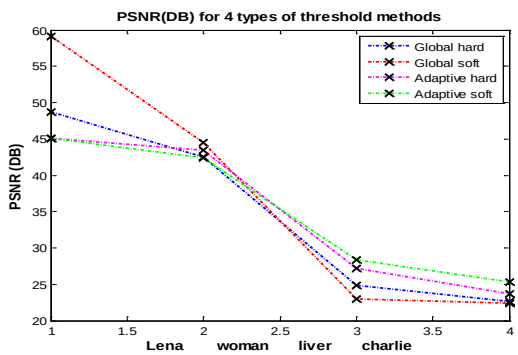

Fig. 10:PSNR value plots for images using HAAR at level 5

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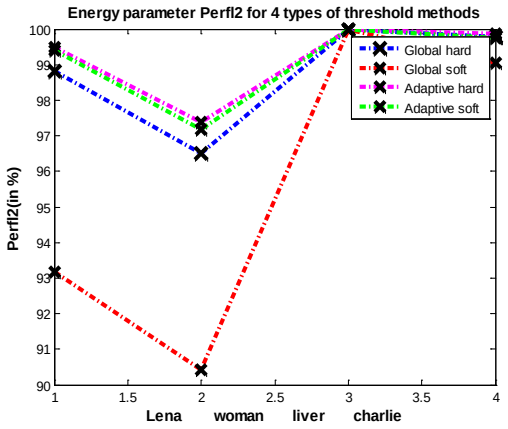

Fig.11: BETA value plots for images using HAAR at level 5

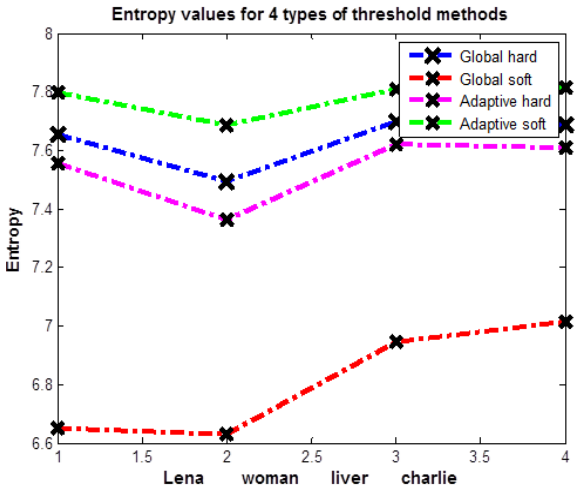

Fig.12:ENTROPY value plots for images using HAAR level 5

From above figures and tables it has been seen that global threshold provide improved results in PSNR values. In hard thresholding, spatial information is more preserved than soft threshold hence results in conservation of better edges as well as noise also. On the other hand soft threshold removes high frequency components i.e. noise very easily and preserve low frequency components i.e. edges, regions etc.

IV. Conclusions

In this work we propose a comparative analysis of the performance of debauchee's wavelet function and Haar after applying wavelet de-noising. The simulation tests have been carried out using different images. Image quality for wavelet function has been evaluated using four different metrics: the peak signal to- noise ratio , mean square error , energy parameter beta and entropy. We have found that Db4 and Haar both are better in removing noise however DB4 gives better results in terms of entropy which measures texture quality in the image. Although the improvement is minor but it is noticeable. Other parameters can also be used for comparing both wavelets but we take entropy as performance measure. Thus we conclude that DB4 better denoise the image than Haar Wavelet. Further, If we compare both hard and soft threshold outputs, hard contains more information as it has high PSNR and BETA parameter but fails in noise reduction. On the other hand soft threshold provides better noise-reduction but has lost some significant spatial information due to low BETA factor. So, in hard thresholding, spatial information is more preserved as compared to the soft threshold hence results in conservation of edges as well as noise also .

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