Improved Image Denoising Technique Using Neighboring Wavelet Coefficients of Optimal Wavelet with Adaptive Thresholding

Rakesh Kumar and B. S. Saini

***Abstract*—These Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising applications. But the optimal choice of the wavelet and thresholding function has restricted there wide spread use in image denoising application. The aim of this paper is twofold; firstly to suggest some new thresholding method for image denoising in the wavelet domain by keeping into consideration the shortcomings of conventional methods and secondly to explore the optimal wavelet for image denoising. In this paper we proposed a computationally more efficient thresholding scheme by incorporating the neighbouring wavelet coefficients, with different threshold value for different sub bands and it is based on generalized Gaussian Distribution (GGD) modeling of sub band coefficients. In this proposed method, the choice of the threshold estimation is carried out by analyzing the statistical parameters of the wavelet sub band coefficients like standard deviation, arithmetic mean and geometrical mean. It is demonstrated that our proposed method performs better than: VisuShrink, Normalshrink and NeighShrink algorithms in terms of PSNR ratio. Further a comparative analysis has been made between Daubechies, Haar, Symlet and Coiflet wavelets to explore the optimum wavelet for image denoising with respect to Lena image. It has been found that with Coiflet wavelet higher PSNR ratio is achieved than others. Hence proposed for denoising the Lena image.**

***Index Terms*—Image denoising, gaussian noise, thresholding, neighbouring coofficients, wavelet.**

I. Introduction

An image is often corrupted by noise in its acquisition or transmission. The goal of denoising method is to remove the noise while retaining as much as possible of the important image features. Traditionally, this is achieved by linear processing such as Wiener filtering but now a days wavelet transform (WT), due to its excellent localization property, has rapidly become an indispensable image processing tool for variety of applications, including compression and denoising [1]-[3]. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. It involves three steps: a linear forward wavelet transform, nonlinear wavelet thresholding steps and a linear inverse wavelet transform. The wavelet thresholding (first proposed by Donoho [1]-[3] is a signal estimation technique that exploits the capabilities of WT for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold, and turns out to be simple and effective, depends heavily on the choice of this threshold determines, to a great extent the efficiency of denoising. Researchers have developed various techniques for selecting denoising parameters and so far there is no "best" universal threshold determination technique. In the first phase of this paper, a near optimal threshold estimation technique for image denoising, with a modification in the existing NeighShrink algorithm, is proposed by embedding the effect of neighbouring wavelet coefficients with adaptive thresholding.

Further many methods based on WT has been used in past for denoising the images. It has been observed that in all the cases the mother wavelet is selected randomly from the list of vast variety of wavelets without knowing which one produces best results or the same wavelet is used for different types of standard images like Lena, Barbara, Goldhill, Cameraman, Tire etc. But it is well known that every wavelet basis function is designed for any particular form of dynamic [4] thus selecting the same basic function for all the images under test may not be an appropriate choice for image denoising applications. Thus the aim of this part of work is to find an optimal wavelet for denoising the Lena image

II. Discrete Wavelet Transform

The discrete wavelet transform (DWT) [5],[6] of an image generate its non-redundant representation [7] that provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Laplacian pyramid etc. Due to the decomposition of an image using the DWT [8] the original image is transformed into four sub bands which is normally labeled as LL1, LH1, HL1 and HH1 as shown in Fig.1a, The LL1 sub band comes from low pass filtering in both directions and it is the most like original picture and so it is called the approximation. The remaining sub bands are called detailed sub bands. The HL1 comes from low pass filtering in the vertical direction and high pass filtering in the horizontal direction and so has

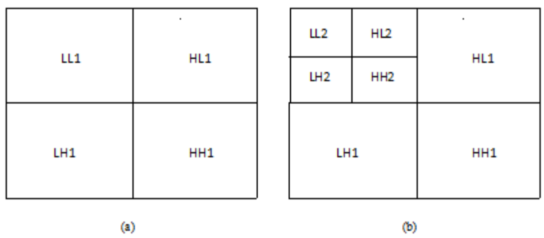

Fig. 1. DWT based image decomposition (a) One level decomposition (b)Two level decomposition

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The authors are with the National Institute of Technology, Jalandhar 144 011, India (e-mail: rakeshdp86@gmail.com, sainibss@gmail.com).

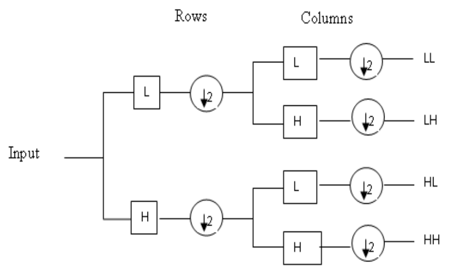

Fig. 2. One level decomposition step of two dimensional image using DWT

the label HL1, it is also known as the horizontal fluctuation. The LH1 sub band comes from high pass filtering in the vertical direction and low pass filtering in the horizontal direction so it is labeled by LH1, it is also known as the vertical fluctuation and the HH1 sub band labeled by HH1 and it is also known as the comes from high pass filtering in both direction so it is Diagonal Fluctuation. The filters L and H shown in Fig. 2 are one-dimensional low pass filter (LPF) and high pass filter (HPF) respectively for image decomposition. To obtain the next level of decomposition, sub band LL1 alone is further decomposed into four subbands labeled as LL2, LH2, HL2 and HH2 as shown in Fig. 2 This process continues until some final scale is reached. After L decompositions, a total of D(L) = 3 * L + 1 sub bands are obtained.

The decomposed image can be reconstructed using a reconstruction filter as shown in Fig. 3. Here, the filters L and H represent low pass and high pass reconstruction filters respectively.

III. Wavelet Thresholding

Let $\{A = A_{i,j}, i, j = 1,2,....N\}$ denotes N x N matrix of an original image and N is integer power of 2. During the transmission, the signal A is corrupted by independent and identically distributed zero mean, white Gaussian noise $n_{i,j}$ with standard deviation σ i.e., $n_{i,j}$ ~ N(0, σ^2) and at the receiver end, the noisy observation $B_{i,j} = A_{i,j} + n_{i,j}$ is obtained. The aim here is to estimate the signal $A_{i,j}$ from the noisy observations $B_{i,j}$ such that the peak signal to noise ratio (PSNR) is maximum.

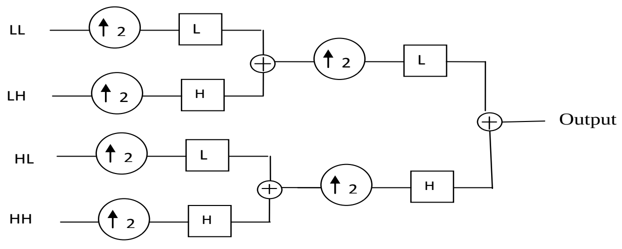

Fig. 3. One level reconstruction step of two dimensional image using IDWT

In order to achieve this $B_{i,j}$ is transformed into wavelet domain that decomposes $B_{i,j}$ into many sub bands as shown in Fig. 2, which separates the signal into so many frequency bands. Further, the coefficients with a smaller value in the sub bands are dominated by noise, while coefficients with large absolute value carry more signal information than noise. Thus, replacing noisy coefficients (small coefficients below certain value) by zero and an inverse wavelet transform may lead to reconstruction that has lesser noise. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. The hard and soft thresholding [9],[10] operators with threshold λ are defined using (1) and (2).

$$\eta(d) = [(d_i),]|d_i| \geq \lambda$$
$$and[0],|d_i| \leq \lambda \tag{1}$$

$$\eta(d) = [sign(d_i).(|d_i| - \lambda)],|d_i| \geq \lambda$$
$$and = [0],|d_i| \leq \lambda \tag{2}$$

where d_i is the input and are the noisy wavelet coefficients, available in the detailed sub bands as defined in Fig. 2, which are to be thresholded, λ is the threshold value and η(d) is the thresholded output which is used to estimate the noiseless coefficients.

The hard (based on keep and kill rule) can be unstable or more sensitive to small changes in the data, while soft thresholding (based on shrink and kill rule) avoid discontinuities and is therefore more stable than hard thresholding.

IV. Image Denoisng Using Thresholding

In image denoising applications the selection of the threshold value should be such that the peak signal to noise ratio (PSNR) is maximized. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details and hence both these values results in poor denoising. The methods used for the thresholding and its selection in accordance with the standard Lena image is explained as follows:

A. *VisuShrink Algorithm (VS)*

VS is thresholding by applying the universal threshold proposed by Donoho and Johnstone [11]. This threshold is given by $\lambda = \sigma\sqrt{2\log n^2}$, where σ is the noise level and n is the length of the noisy signal.

A. *NormalShrink Algorithm (NS)*

It is based on the generalized Gaussian distribution (GGD) modeling of sub band coefficients [12], [13]. The threshold λ is computed using (3)

$$\lambda = \beta\sigma^2 / \sigma_y \tag{3}$$

where, β is the scale parameter and is computed once for every scale using (4), σ_y is the standard deviation of the sub band under consideration, σ^2 is the noise variance which is estimated from the sub band HH_1 using (5)

$$\beta = \sqrt{\log\left(J_k / L\right)} \tag{4}$$

where J_k is the length of the subband at k^{th} scale, L is the number of decomposition level.

$$\sigma^2 = \left| \frac{median|y_{i,j}|}{.6745} \right|^2 \tag{5}$$

where $y_{i,j} \varepsilon$ sub band HH_1

B. NeighShrink Algorithm (NGS)

Cai *et. al.* [14] observed that the wavelet coefficients are correlated in a small neighbourhood. A large wavelet coefficient will probably have large coefficients at its neighbours and vice versa. Thus the procedure which is adopted here to implement NGS by incorporating neighbouring coefficients [14] in the thresholding process is as follows:

Suppose $w_{(i,j)}$ is the set of wavelet coefficients of the noisy 1D signal. If

$$s^2_{(i,j)} = w^2_{(i,j-1)} + w^2_{(i,j)} + w^2_{(i,j+1)} \tag{6}$$

is less than or equal to λ^2, where $\lambda = \sigma\sqrt{2\log n}$, and n is the length of the signal, then we set the wavelet coefficient w(i,j) to zero. Otherwise, we shrink it according to (7)

$$w_{(i,j)} = w_{(i,j)}\left(1 - \frac{\lambda^2}{s^2_{(i,j)}}\right) \tag{7}$$

Note that we should omit the first (last) term in (6), if $w_{(i,j)}$ is at the left (right) boundary of level j wavelet coefficients.

For image denoising as explained earlier, we have to do a 2D wavelet transform. In this algorithm for every detail wavelet coefficient $w_{(i,j)}$ of our interest, we need to consider a neighborhood window $B_{(i,j)}$ around it [15],[16]. We choose the window by having the same number of pixels above, below, on the left or right of the pixel to be thresholded. That means the neighbourhood window size can be 3×3 or 5×5 or 7×7 or 9×9 etc. But in this work we select a 3× 3 neighbourhood window, shown in Fig. 4, center at the wavelet coefficient to be thresholded and we threshold different wavelet coefficient sub bands independently.

$$\text{Let } s^2_{(i,j)} = \sum w^2_{(i,j)} \tag{8}$$

When the (8) summation has pixel indices out of the wavelet sub band range, we omit the corresponding terms in the summation. For the wavelet coefficient to be thresholded, we shrinkage it according to the (9)

$$\hat{w}_{(i,j)} = w_{(i,j)} * B_{(i,j)} \tag{9}$$

where the shrinkage factor $B_{(i,j)}$ can be defined as

$$B_{(i.j)} = \left(1 - \lambda^2 / s^2_{(i,j)}\right)_+ \tag{10}$$

where $\lambda = \sigma\sqrt{2\log n^2}$

and n is the length of the signal

Here, the + sign at end of the equation means to keep the positive value, while set it to zero when it is negative.

C. Proposed Algorithm

The NGS algorithm explained above has an added advantage over the VS and NS algorithms in the form of considering the effect of neighboring wavelet coefficients in image denoising using thresholding. Further, in the NeighShrink algorithm the threshold value λ as per (12) is kept constant for every detailed sub bands. But different sub bands possess different scaling and translation properties and have variable resolutions. Moreover the value of pixels of every detailed sub band image is different from each other. Thus it is not meaningful to use the same threshold value for all the sub bands rather every sub band should have its own threshold value depending upon its location in the DWT structure - named an adaptive thresholding.

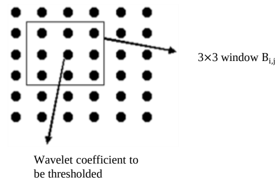

Fig. 4. 3×3 neighbourhood window of the wavelet coefficient to be thresholded

The aim of this part of the paper is to propose a new method to, gain the advantages of neighboring wavelet coefficients i.e., NGS algorithm and adaptive thresholding in image denoising applications. In the proposed method the threshold estimation is carried out by analyzing the statistical parameters of the wavelet sub band coefficients like standard deviation, arithmetic mean and geometrical mean as given in (12).

$$\lambda = C\sigma - (|AM - GM|) \tag{12}$$

Here σ is the noise level of the noisy image.

Normally in wavelet sub bands, as the level increases the coefficients of the sub band becomes smoother. For example the sub band HL2 is smoother than the corresponding sub band in the first level (HL1) and so the threshold value of HL2 should be smaller than that for HL1. The term C is included for this purpose to make the threshold value as decomposition level dependent, which is defined using (13)

$$C = 2^{(L-k)} \tag{13}$$

where L is the number of wavelet decomposition level and k is the level at which the sub band is available.

The arithmetic mean and geometric mean of the sub band noisy wavelet coefficients $w_{(i,j)}$ are denoted using (14) and (15)

$$\text{Arithmetic Mean (AM)} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} w_{(i,j)}}{M^2} \tag{14}$$

$$\text{Geometric Mean (GM)} = \left[\prod_{i=1}^{m}\prod_{j=1}^{m} w_{(i,j)}\right]^{\frac{1}{M^2}} \tag{15}$$

Steps to implement the proposed Algorithm:

Step 1: Perform the DWT of the noisy image upto L=3 levels to obtain (3L+1) sub bands.

Step 2: Compute the threshold value for each sub band, except the LL3 sub band using (13) after finding out its' following terms (i) Obtain the noise level σ using equation (5) (ii) Find the term C for each sub band using (13) (iii) Calculate the term |AM-GM| for each sub band (except approximate coefficients sub band) using (14) and (15).

Step 3: Compute the shrinkage factor using (10)

Step 4: Find out the noiseless wavelet coefficients for all sub bands using equation (9)

Step 5: Perform the inverse DWT

V. NEED FOR OPTIMAL WAVELET

The optimal selection of wavelet has constrained the use of WT in image processing applications. As, there exists an abundant variety of wavelets each is having their own dynamics and characteristics [4] and therefore there is a fundamental problem of determining which one produces appropriate results for a particular application. However it is expected that the suitable wavelet depends on the specific features of the image under test and, thus the image based selection of the mother wavelet is necessary for optimal results with respect to minimizing the reconstruction error. A mother wavelet that matches the image of interest would produce a sharper peak in time-scale space and enhances its ability to better detect the image features. Thus finding a wavelet that can provide the proper estimation for a given Lena image is the aim of this part of paper. In this reference several standard wavelet families are tried like Daubechies, Haar, coiflet and symlet and the one which produces best results is proposed.

VI. RESULTS AND DISCUSSIONS

In this part of paper in order to prove the superiority of our proposed denoising method all the above mentioned algorithms have been applied on the same natural gray scale standard test image Lena of size 512x512 shown in Fig. 5

All these methods are tested for 10 different levels of Gaussian noise i.e. 10, 15, 20, 25, 30, 35, 40, 45 50 and 55 respectively and the corresponding 10 different Gaussian noise corrupted images on the same natural gray scale standard test image Lena of size 512x512 shown in Fig. 5

Fig. 5. Natural gray scale standard test image Lena of size 512x512

All these methods are tested for 10 different levels of Gaussian noise i.e. 10, 15, 20, 25, 30, 35, 40, 45 50 and 55 respectively and the corresponding 10 different Gaussian noise corrupted images are shown in Fig 6.

Fig. 6. Gaussian noise corrupted images for different noise levels (a) Level 10 (b) Level 15 (c) Level 20 (d) Level 25 (e) Level 30 (f) Level 35 (g) Level 40 (h) Level 45 (i) Level 50 (j) Level 55

The performances of these denoising algorithms have been evaluated by computing the PSNR using (16)

$$PSNR = 10\log_{10}\frac{255^2}{MSE}dB \qquad (16)$$

where MSE is the mean square error of the image and it is computed using (17)

$$MSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\left(x(i,j) - B(i,j)\right)^2}{MN} \qquad (17)$$

where x(i,j)is the denoised image and B(i,j) is the noisy image.

TABLE I: THE COMPARATIVE ANALYSIS BETWEEN VISUSHRINK, NORMALSHRINK, NEIGHSHRINK AND OUR PROPOSED METHOD IN THE TERMS OF PSNR FOR DB-3 WAVELET

S.No	Noise levels	PSNR of noisy images	PSNR of denoised images using different algorithms			
			VS	NS	NGS	Proposed Method
1.	10	28.1308	30.2284	30.5800	32.8752	33.2225
2.	15	24.6090	28.847	29.1819	31.1083	31.6072
3.	20	22.1102	27.9159	28.2389	29.8141	30.4287
4.	25	20.1720	27.2314	27.5318	28.8244	29.4874
5.	30	18.5884	26.7004	26.9726	28.0278	28.7112
6.	35	17.2494	26.2656	26.5218	27.3565	28.0497
7.	40	16.0896	25.8903	26.1248	26.7904	27.475
8.	45	15.0666	25.5536	25.7735	26.3054	26.961
9.	50	14.1514	25.2454	25.4473	25.8794	26.4962
10	55	13.3236	24.9631	25.1435	25.502	26.0742

VS: Visushrink Algorithm NS: Normalshrink Algorithm, NGS: NeighShrink Algorithm

A comparative analysis has been performed between VS, NS, NGS and our proposed method and the results in the form of PSNR are given in Table 1 for 10 different levels of Gaussian noise for Db-3 wavelet. It is observed that as the level of Gaussian noise gets increased from 10 to 55 the PSNR of noisy images go on reducing and an improvement in terms of PSNR is observed after applying VS algorithm on noisy images (See Table 1) and also shown by a line with triangles on it in Fig. 7, the PSNR ratio gets further improved from that obtained with NS algorithm (See Table 1), and the same trend in Fig. 7 is observed by a line with bubbles on it. On applying the NGS algorithm the PSNR gets further enhanced. The similar trend in the PSNR is seen in Fig. 7 by a line with crosses on it. When our proposed method is applied on all the 10 noisy images a significant increase in PSNR is obtained in comparison to VS, NS, NGS algorithms (See Table 1) and shown by plotting a line with squares on it. This demonstrates a significant improvement in image quality.

TABLE II: COMPARATIVE ANALYSIS BETWEEN DIFFERENT WAVELET FAMILIES BY USING OUR PROPOSED METHOD IN THE TERMS OF PSNR

S.No	Noise levels	PSNR of noisy images	PSNR of denoised images using our proposed method for different wavelet families			
			Db Db-5	Haar	Coif Coif-5	Sym Sym-5
1.	10	28.1308	33.6068	32.8044	33.7213	33.6029
2.	15	24.6090	32.2153	31.2054	32.3454	32.252
3.	20	22.1102	31.005	30.016	31.2648	31.166
4.	25	20.1720	30.1696	29.0808	30.34	30.2424
5.	30	18.5884	29.3728	28.3075	29.5262	29.437
6.	35	17.2494	28.657	27.6504	28.8105	28.7255
7.	40	16.0896	28.0254	27.0608	28.1548	28.0829
8.	45	15.0666	27.4408	26.5342	27.5615	27.4958
9.	50	14.1514	26.8964	26.047	27.016	26.9525
10.	55	13.3236	26.3936	25.5914	26.5119	26.4479

Db: Daubechies Wavelet, Haar: Haar wavelet, Coif: Coiflet wavelet, Sym: Symlet wavelet

In addition, the superiority of our proposed method is established by actually performing the comprehensive study on Daubechies wavelets (Db-2 to Db-10), Haar wavelet, Coiflet wavelets (Coif-1 to Coif-5), Symlet wavelets (Sym-2 to Sym-8) in addition to Db-3 wavelet. But here we are only producing the results for Db-3 wavelet.

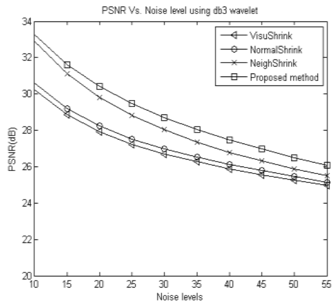

Fig. 7. Trend in the values of PSNR obtained using using different denoising algorithms for 10 different noise levels

Further, in this paper as we are using different types of wavelets, an attempt has been made to explore the optimal wavelet to efficiently denoise the image. Here in this part of paper in order to detect the Lena image specific wavelet a comparative study has performed between Daubechies, Haar, coiflet and symlet wavelet families for the same filter length of N=5. We are here showing the results, given in Table 2, of all these wavelets on only our proposed method. After verifying the results it is demonstrated that the coiflet wavelet of filter length 5 (coif-5) shows the better performance in terms of higher PSNR of denoised image in comparison to Daubechies, Haar, and symlet wavelets. In addition, the same study has also extended to VS, NS, NGS algorithms for finding the superiority of coif-5 wavelet over others and the same observations were obtained.

VII. CONCLUSION

Since the proposed method gain the merits of both neighboring wavelet coefficients and adaptive thresholding of the sub band coefficients, it is more efficient. Experiments are conducted on standard image Lena using10 different noise levels to access the performance of proposed method in comparison to conventional methods for 22 different wavelets. It is verified that our method performs better in denoising of corrupted images by possessing higher PSNR. Currently, most of the images were being analyzed using the same wavelet. This approach although attractive in its simplicity, but may not fit appropriate to use the same wavelet for all the images. Thus an effort has been made to find the optimal wavelet for denoising the Lena image. It has been found that coif-5 wavelet gives higher PSNR.

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B S Saini was born in Jalandhar, India, in 1970. He received his B.Tech degree in Electronics and Communication Engineering from Gulbarga University, India in 1994, M.Tech. degree in Electronics and Communication Engineering from Kurukshetra University, India in 1996 and Ph.D. degree in the area of Signal Processing of heart rate variability from NIT Jalandhar, India, in 2009.

He is serving as Associate Professor in Electronics and Communication Engineering Department, NIT Jalandhar, India from last 15 years. His research interests includes Biomedical Signal Processing, Image Processing, Microprocessors and Microcontrollers, Soft Computing.

Mr Saini is a member of IEEE, IEEE EMBS, Fellow IETE. He has guided more that 20 MTech students and guiding 06 PhD research scholars. He has published more that 20 research papers in International Journals of repute.

Rakesh kumar was born on August 15, 1986 in Pilani, India. He received his Bachelor of Engineering (B.E) degree from University of Rajasthan, Jaipur, India in 2008, and M.Tech degree from Dr. B R Ambedkar National Institute of Technology, Jalandhar, India in 2010, both in Electronics and Communication Engineering. Since August 2011, he has been working as Assistant professor in the Department of Electronics and Communication Engineering at Shridhar University, Pilani, India. He has published international papers on Image denoising and his research specialization is in the same field.