Investigation Of Optimal Wavelet Family To Improve The Psnr Of Digital Image

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Abstract

Denoising is the process of removing noise from image.Additive noise can be easily removed using simple threshold methods.Denoising of natural images corrupted by Gaussian noise using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values.DWT supports multiresolution property which is not supported by another techniques(fourier transform).In this paper the visushrink, normalshrink, neighshrink and revised neighshrink methods are compared to get the better value of PSNR.Observed result shows that the revised neighshrink gives better result in terms of PSNR.

Keywords: Image,denoising, wavelet transform, VS, NS, NGS,RNGS, PSNR.

1.Introduction

Image noise is unwanted energy value in pixel intensity values. The noise is considered as a high-frequency component in the transform domain for both fast Fourier transform (FFT) and discrete wavelet transform (DWT) and hence thresholding or truncating eliminates noise.Wavelets are mathematical functions that analyze data according to scale or resolution.They aid in studying a signal in different windows or at different resolutions. “wavelets” is used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ . The finite scale multiresolution representation of a discrete function can be called as a discrete wavelet transform. DWT is a fast linear operation on a data vector, whose length is an integer power of 2.Basic wavelet image restoration methods are based on thresholding in the sense that each wavelet coefficient of the image is compared to a given threshold.This paper describes the visushrink, neighshrink and revised neighshrink methods which uses the soft thresholding(Soft thresholding method is baesd on the Kill or Shrink rule).Wavelet transform have received a lot of attention in many areas like multiresolution analysis,image compression,image enhancement etc.Decomposition is done by scaling and translation.Denoising is done by DWT has many advantages over fourier transform and continuous wavelet transform.There are two basic approaches to image denoising, spatial domain methods and transform domain methods. The main difference between these two categories is that a transform domain method decomposes the image by a chosen basis before further processing while a spatial domain method processes the observed image data directly.Simple denoising algorithms uses the following steps to denoise image.

1.Calculate:
Calculate the wavelet transform of noisy image.

2.Modify:Modify the noisy wavelet coefficients according to some rule.

3.Compute:Compute the inverse transform using the modified coefficients.

Image denoising can be described as follows:

Let A(i,j) be the noise-free image and B(i,j) the image corrupted with independent gaussian noise Z(i,j).

$$\mathbf{B_{i,j} = A_{i,j} + \sigma Z_{i,j}} \qquad .....(1.1)$$

Z(I,j) has normal distribution N(0,1).In the wavelet domain the problem can be formulated as

Y(I,j)=W(I,j)+N(I,j) .....(1.2)

Where Y(I,j) is noisy wavelet coefficient;W(I,j) is true coefficient and N(I,j) is independent Gaussian noise.In this paper the performance of PSNR is evaluated using different algorithms and shows the improved value of the PSNR.

2.Related Work

A new fast and efficient algorithm capable in removing Gaussian noise with less computational complexity. This algorithm initially estimates the amount of noise corruption from the image and then the center pixel value is replaced by mean value of the surrounding pixels based on the threshold value [1].Image denoising can be easily removed using simple threshold methods.Denoising of images using DWT is very effective because of its ability to capture the energy of a signal in few energy transform values [2].
This paper describes the relationship of discrete and continuous wavelet transform.It focuses on bringing together two separately motivated implementations of the wavelet transform[4].Various conventional wavelet denoising approaches like VisuShrink, Normalshrink and NeighShrink algorithm which is based on neighbouring wavelet coefficients with universal threshold,which gives significant improvement of Mean Square Error (MSE) [3].

3.Methodology Used

3.1 Discrete Wavelet Transform

The wavelet transform is a recently developed mathematical tool that provides a non uniform division of data or signal, into different frequency components, and then studies each component with a resolution matched to its scale. It is often used in the analysis of transient signals because of its ability to extract both time and frequency information simultaneously, from such signals.

3.1.1 FDWT

FDWT stands for forward discrete wavelet transform. It is the transformation of sampled data, e.g. transformation of values in an array, into wavelet coefficients.

3.1.2 IDWT

IDWT stands for inverse discrete wavelet transform. It converts wavelet coefficients into the original sampled data.

3.2 Threshold Selection:

Threshold selection play an important role when applying the wavelet thresholding scheme. A small threshold may yield a result close to the input, but the result may be still be noisy. A large threshold produces a signal with a large number of zero coefficients. This leads to an overly smooth signal and smoothness generally suppresses the details and edges of the original signal and causes blurring and ringing artifact.

3.2.1 VisuShrink Algorithm

For VisuShrink algorithm , the wavelet coefficients'd' of the noisy signal are obtained first.Then with the universal threshold $\lambda = \sigma\sqrt{2\log n^2}$, ($\sigma$ is the noise level and n is the length of the noisy signal) the coefficients d= $\{d_i\}$, where i = 1, 2. . . n are shrinked according to the soft-shrinkage rule or soft thresholding methodgiven

$$\eta(d) = \begin{cases} \text{sign}(d_i).(|d_i| - \lambda), & |d_i| \geq \lambda \\ 0, & |d_i| < \lambda \end{cases}$$

3.2.2 NeighShrink Algorithm

NeighShrink algorithm threshold the wavelet coefficients according to the magnitude of the square sum of all the wavelet coefficients within the neighbourhood window.It is based on the incorporating neighbouring wavelet coefficients with universal threshold. The NeighShrink algorithm is described as follows.

3.2.2.1 Incorporating Neighbouring Wavelet Coefficients

The wavelet transform can be accomplished by applying the low-pass and high-pass filters on the same set of low frequency coefficients recursively. That means wavelet coefficients are correlated in a small neighbourhood. A large wavelet coefficient will probably have large coefficients at its neighbour locations. Therefore, Cai et al. [23] proposed the following wavelet denoising scheme for 1D signal by incorporating neighbouring coefficients into the thresholding process.

Let $d_{j,k}$ is the set of wavelet coefficients of the noisy 1D signal than in equation 3.1

$$\mathbf{s^2_{(j,k)} = d^2_{(j,k-1)} + d^2_{(j,k)} + d^2_{(j,k+1)}} \quad (3.1)$$

If $s^2_{(j,k)}$is less than or equal toλ^2, then set the wavelet coefficient $d_{j,k}$ to zero. Otherwise, these coefficients shrink according to equation 3.2

$$\mathbf{D_{j,k} = d_{j,k}(1\text{-}\lambda^2/\, s^2_{(j,k)})} \quad (3.2)$$

Where $\lambda = \sigma\sqrt{2\log n}$ and 'n' is the length of the signal. Note that the first (last) term in $s^2_{(j,k)}$ is omit if $d_{j,k}$ is at the left (right) boundary of level j wavelet coefficients. For image denoising, the wavelet coefficients are arranged as a square matrix. For every level of wavelet decomposition, first produce four frequency subbands, namely, LL, LH, HL, and HH. Since the Gaussian noise will be averaged out in the low frequency wavelet coefficients, so keep the small coefficients in these frequencies, only wavelet coefficients in the high frequency levels need to be threshold. That means only the high frequency subbands LH, HL and HH need to be thresholded. For every wavelet coefficient $d_{j,k}$ of our interest, so consider a neighbourhood window $Q_{j,k}$ around it [24] and choose the window by having the same number of pixels above, below, and on the left or right of the pixel to be threshold. That means the neighbourhood window size should be 3 × 3, 5 × 5, 7 × 7, 9 × 9, etc. figure 2.2 illustrates a 3 × 3 neighbourhood window centered at the wavelet coefficient to be thresholded. It should be mentioned in this algorithm that different wavelet coefficient subbands are threshold independently. This means when the small window surrounding the wavelet coefficient to be thresholded touches the coefficients in other subbands, we do not include those coefficients in the calculation. For 2D the square of summation around the window of wavelet coefficients is given by equation 3.3.

$$\mathbf{s^2}_{(\mathbf{j,k})} = \sum_{(\mathbf{j,k})\varepsilon \mathbf{Q_{j,k}}} \mathbf{d^2}_{(\mathbf{j,k})} \quad (3.3)$$

Where $d_{j,k}$ is the wavelet coefficient after 2D discrete wavelet transform and $Q_{j,k}$ is the window size centered at the wavelet coefficients to be thresholded as shown in figure 2.2.

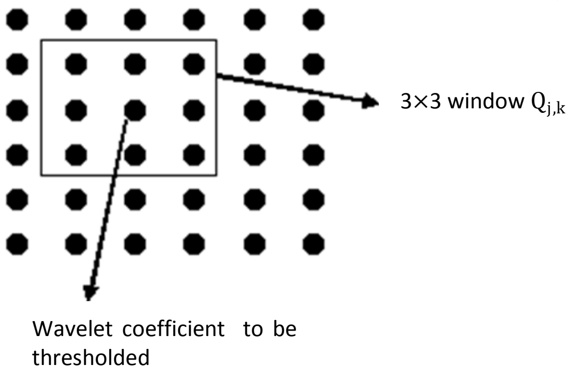

Figure 3.1 An illustration of the neighbourhood window centered at the wavelet coefficient to be thresholded .

When the above summation has pixel indices out of the wavelet subband range, the corresponding terms in the summation is omitted.

For the wavelet coefficient to be thresholded [25], it is shrinked according to the following equation 3.4

$$\widehat{\mathbf{d_{j,k}}} = \mathbf{d_{j,k}}\mathbf{Q_{j,k}} \quad (3.4)$$

Where the shrinkage factor can be defined as equation 3.5

$$\mathbf{Q_{j,k}} = (\mathbf{1} - \boldsymbol{\lambda}^2 / \mathbf{s^2}_{(\mathbf{j,k})})_+ \quad (3.5)$$

Here, the + sign in the formula means it takes nonnegative value, and $\lambda = \sigma\sqrt{2\log n^2}$ is the threshold for the image. This thresholding formula is a modification to the classical soft thresholding scheme developed by Donoho and his co-workers[14]. The neighbourhood window size around the wavelet coefficient to be thresholded has influence on the denoising ability of this algorithm. The larger the window size, the relatively smaller the threshold, If the size of the window around the pixel is too large, a lot of noise will be kept, so an intermediate window size of 3 × 3 or 5 × 5 should be used. The neighbour wavelet image denoising algorithm can be described as follows:

(1) Perform forward 2D wavelet decomposition on the noisy image.

(2) Apply the proposed shrinkage scheme to threshold the wavelet coefficients using a neighbourhood window $Q_{j,k}$and the universal threshold $\sigma\sqrt{2\log n^2}$

(3) Perform inverse 2D wavelet transform on the thresholded wavelet coefficients.

This algorithm is known as NeighShrink algorithm. Because VisuShrink algorithm kills too many small wavelet coefficients, so this shrinkage schemes gives the better result.

3.2.2.2 Limitation of NeighShrink Algorithm:

In the above mention that this algorithm is based on soft thresholding technique that is based on kill or shrink rule according to the wavelet coefficients and threshold value but it is use the universal threshold for every subbands. Normally in wavelet subbands, as the level increases the coefficients of the subband becomes smoother [1]. For example the subband HL2 is smoother than the corresponding subband in the first level (HL1) and so the threshold value of HL2 should be smaller than that for HL1. This is the limitation of this method which is use universal threshold for every subbands. This limitation is overcome in our proposed method. In propose proposed method we take the NeighShrink algorithm with different threshold value for different subbands which is based on Generalized Gaussian Distribution (GGD) modeling of subband coefficients.

3.2.3 Revised NeighdShrinkAlgorithm(proposed method)

In the NeighShrink algorithm different wavelet coefficient subbands are shrinked independently, but the threshold λ keep unchanged in all subbands. The shortcoming of this method is that the threshold λ in all subbands is suboptimal. The optimal λ of every subband should be data-driven and maximize the peak signal to noise ratio (PSNR). We will improve NeighShrink by determining an optimal threshold for every wavelet subbandwhich is based on Generalized Gaussian Distribution (GGD) modeling of subband coefficients. In this proposed method, the choice of the threshold (λ) estimation is carried out by analyzing the statistical parameters of the wavelet subband coefficients like standard deviation, arithmetic mean and geometrical mean as shown in equation 3.6

$$\Lambda = C(\sigma - (|AM-GM|) \qquad (3.6)$$

Here σ is the noise variance of the corrupted image [21],[22] .

The term C is depend on number of decomposition level and the level where the subband is available at that time which is given in equation 3.7.

$$C = 2^{(L-k)} \qquad (3.7)$$

Where, L is the no. of wavelet decomposition level, k is the level at which the subband is available.

The Arithmetic Mean and Geometric Mean of the subband matrix $d_{(j,k)}$ are given in equation 3.8 and 3.9.

$$\text{Arithmetic Mean} = \frac{\sum_{j=1}^{m} \cdot \sum_{k=1}^{m} d_{(j,k)}}{M^2} \qquad (3.8)$$

$$\text{Geometric Mean} = \left[\prod_{j=1}^{m} \cdot \prod_{k=1}^{m} d_{(j,k)}\right]^{\frac{1}{M^2}} \qquad (3.9)$$

Steps of Revised NeighShrink algorithm:

The Complete algorithm of proposed wavelet based image denoising technique is explained in the following steps.

(1) Perform the DWT of the noisy image using Mallat algorithm [18] upto L levels to obtain (3L+1) subbands, for L=2 levels subbands are named as HH1, LH1, HL1, HH2, LH2, HL2 and LL2.In figure 3.2 the LL1, LH1, HL1 and HH1 be the four subbands of image after first decomposition step and LL1LL2, LL1LH2, LL1HL2, LL1HH2 are the four subbands of image when LL1 subband is decomposed in second decomposition step. Similarly LH1LL2, LH1LH2, LH1HL2, LH1HH2 be the subbands when LH1 is decomposed in second step. HL1LL2, HL1LH2, HL1HL2, HL1HH2, be the subbands when HL1 is decomposed in second step and HH1LL2, HH1LH2, HH1HL2, HH1HH2 are the subbands when HH1 is decomposed. The total no. of subbands after second decomposition level is 16. After L decompositions, a total of D(L) = subbands are obtained. Where L is the no. of decomposition level.

LL1LL2	LL1HL2	HL1LL2	HL1HL2
LL1LH2	LL1HH2	HL1LH2	HL1HH2
LH1LL2	LH1HL2	HH1LL2	HH1HL2
LH1LH2	LH1HH2	HH1LH2	HH1HH2

Fig 3.2 Subband structure after two level packet decomposition.

(2) Compute the threshold value for each subband, except the approximate coefficients band using equation (3.5) after finding out its' following terms.Obtain the noise variance from equation (3.10) Find the term C for each subband using equation [3.1] (3.7).Calculate the term |AM-GM| for each subband (except approximate coefficients subband) using equations (3.8) and (3.9).

(3) Put the threshold value in equation [3.9] (3.5) of all subband coefficients (except approximate coefficients subband) for calculating the shrinkage factor. And then find the noiseless coefficient using equation (3.4)

(4) Perform the inverse DWT to reconstruct the denoised image.The information from the four sub-images is up-sampled and then filtered with the corresponding inverse filters along the columns The two results that belong together are added and then again up-sampled and filtered with the corresponding inverse filters. The result of the last step is added together in order to get the original image again.

4. RESULTS AND DISCUSSION

Table 4.1 PSNR of the noisy images and denoised images of standard image testpat1 using db2 wavelet

S.No	PSNR of noisy image	PSNR of denoised images using different algorithms			
		VS	NS	NGS	RNGS
1.	28.1308	29.8949	30.2309	32.4999	32.8213
2.	24.6090	28.5275	28.859	30.7384	31.2131
3.	22.1102	27.5958	27.918	29.4632	30.0586
4.	20.1720	26.9114	27.2204	28.4816	29.1379
5.	18.5884	26.3671	26.66	27.6839	28.3762
6.	17.2494	25.919	26.1924	27.0356	27.726
7.	16.0896	25.5376	25.7879	26.4759	27.1634
8.	15.0666	25.2011	25.4325	25.998	26.6609
9.	14.1514	24.8969	25.1057	25.5778	26.2029
10.	13.3236	24.6103	24.8018	25.1954	25.7849

Table 4.2 PSNR of the noisy images and denoised images of standard image testpat1 using haar wavelet

S.No	PSNR of noisy image	PSNR of denoised images using different algorithms			
		VS	NS	NGS	RNGS
1.	28.1308	28.6816	28.996	31.326	31.607
2.	24.6090	27.3526	27.649	29.44	29.8584
3.	22.1102	26.4556	26.754	28.1658	28.6915
4.	20.1720	25.7909	26.0866	27.2156	27.8274
5.	18.5884	25.2714	25.5539	26.4689	27.1257
6.	17.2494	24.8492	25.1108	25.8447	26.5353
7.	16.0896	24.4966	24.7412	25.3135	26.0247
8.	15.0666	24.1836	24.4162	24.8461	25.5681
9.	14.1514	23.9035	24.1233	24.4436	25.151
10.	13.3236	23.6466	23.848	24.0927	24.7723

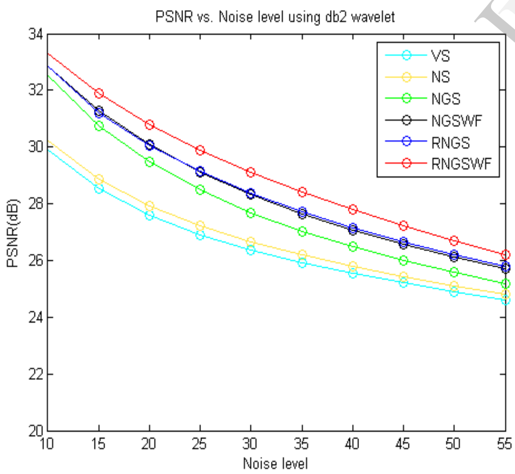

Figure 4.1 PSNR of the noisy images and denoised images of standard image testpat1 using sym2 wavelet.

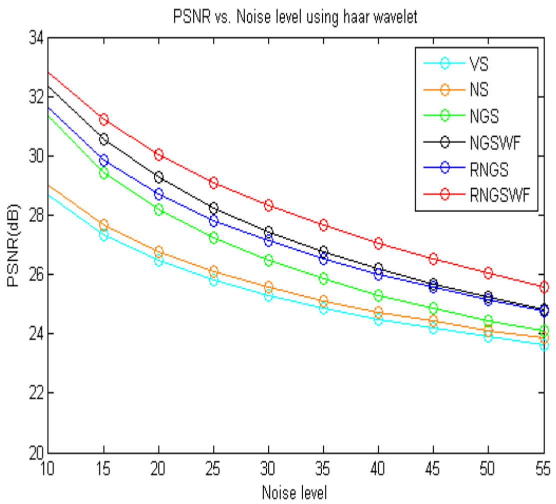

Figure 4.2 PSNR of the noisy images and denoised images of standard image testpat1 using coif1 wavelet.

Table 4.3 PSNR of the noisy images and denoised images of standard image testpat1 using sym2 wavelet

S.No	PSNR of noisy image	PSNR of denoised images using different algorithms			
		VS	NS	NGS	RNGS
1.	28.1308	29.8949	30.2309	32.4999	32.8213
2.	24.6090	28.5275	28.859	30.7384	31.2131
3.	22.1102	27.5958	27.918	29.4632	30.0586
4.	20.1720	26.9114	27.2204	28.4816	29.1379
5.	18.5884	26.3671	26.66	27.6839	28.3762
6.	17.2494	25.919	26.1924	27.0356	27.726
7.	16.0896	25.5376	25.7879	26.4759	27.1634
8.	15.0666	25.2011	25.4325	25.998	26.6609
9.	14.1514	24.8969	25.1057	25.5778	26.2029
10.	13.3236	24.6103	24.8018	25.1954	25.7849

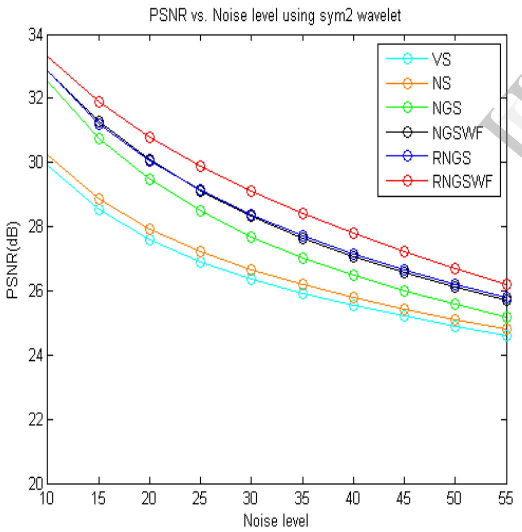

Figure 4.3 PSNR of the noisy images and denoised images of standard image testpat1 using sym2 wavelet.

Table 4.4 PSNR of the noisy images and denoised images of standard image testpat1 using coif1 wavelet

S.No	PSNR of noisy image	PSNR of denoised images using different algorithms			
		VS	NS	NGS	RNGS
1.	28.1308	29.8616	30.1708	32.5007	32.8451
2.	24.6090	28.5204	28.8216	30.7132	31.2034
3.	22.1102	27.6072	27.8995	29.4554	30.0482
4.	20.1720	26.9295	27.2157	28.4855	29.1438
5.	18.5884	26.3865	26.6601	27.6813	28.3944
6.	17.2494	25.936	26.1854	27.0191	27.7428
7.	16.0896	25.5628	25.7887	26.4726	27.1733
8.	15.0666	25.2398	25.44	26.015	26.6612
9.	14.1514	24.9478	25.1319	25.6175	26.2075
10.	13.3236	24.6783	24.8468	25.25	25.805

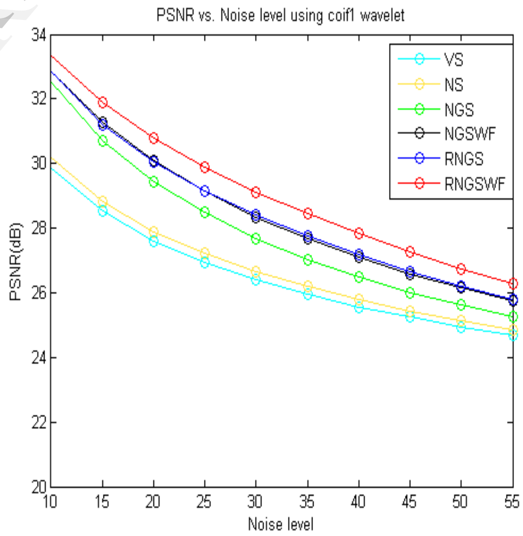

Figure 4.4 PSNR of the noisy images and denoised images of standard image testpat1 using coif1 wavelet.

4. Conclusion:

In this paper work,four conventional denoising algorithms i.e. VisuShrink, Normalshrink, NeighShrink and Revised neighshrink are compared. Out of these four algorithms Revised NeighShrink gives the outstanding result in terms of the PSNR.The conventional NeighShrink algorithm is modified by considering the different threshold value for different subbands that is based on Generalized Gaussian Distribution (GGD) modeling.The results have shown that the denoising of images using the Revised NeighShrink algorithm and the coiflet wavelet gives better result in terms of PSNR.

5. Future Scope

Image processing is an exciting interdisciplinary field as it has wide range of applications in various fields like remote sensing, biomedical, industrial automation, office automation, criminology, military, astronomy, and space. Visual quality of an image may decreases during its sensing, storing, or sending.

Future work may be done for improving the peak signal to noise ratio by considering the wavelet packet,quadrature spline wavelet, adaptive window size.

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