Comparative Study on Natural Image denoising in DWT and Contourlet Transform using Bayes Shrinkage Technique

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Abstract - *Image noise is random variation of brightness or color information in images. There are several types of noise can be introduced in the images during image acquisition,transfer & storage. The main objective is to remove the noise from the input image. Natural image is used as input image. Natural images are always corrupted with Gaussian noise. The input images are taken and then the noise is added in the image. Then apply the DWT and Counterlet transform to the noisy image. Thresholding function is used to identify and filter the noisy co efficient and take inverse transform to reconstruct the original image. To improve the quality of the denoising method the frequency domain is used .The result of the proposed method is compared with the best transform. In this work Bayes shrink(BS) is applied on the transformed image. Finally the performance of the transformed are compared using PSNR.*

***Key Words*: Discrete Wavelet Transform(DWT), Contourlet Transform(CT), Natural Images, Gaussian Noise, Speckle Noise, BayesShrink(BS)**

1.INTRODUCTION

Digital images are often corrupted by many types of noise including Gaussian noise, Speckle noise which are normally acquired during image acquisition and transmission. Image noise is random variation of brightness or Color information in images , and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Speckle noise is also known as multiplicative noise. Gaussian noise is statistical in nature. Its probability density function equal to thatof normal distribution, which is otherwise called as Gaussian distribution. Wavelet is a powerful tool for denoising a variety of signals.The Discrete Wavelet Transform (DWT) has been successfully applied for a wide range of image analysis problems. The Contourlet Transform (CT) which can efficiently contour at multiple resolutions. Wavelet thresholding technique operates on one of the wavelet coefficients at a time. In it the coefficient which is smaller than threshold is set to zero otherwise it is kept or modified [16]. Contourlet thresholding techniques decompose the image into the image coefficients, this image coefficient gets processed by using the thresholding for the restoration of noiseless image coefficients.

1.1. Related Work

Image denoising is an basic and very important steps in image processing. Images are often corrupted with noise during acquisition, transmission, and retrieval from storage media. Many dots can be spotted in a Photograph taken with a digital camera under low lighting conditions. Image denoising is needed because a noisy image is not pleasant to view. In addition, some fine details in the image may be confused with the noise. There are many image processing methods such as Image Enhancement, Image Restoration, Segmentation, Feature Extraction, Pattern Recognition need a clear image to work very effectively. Image denoising is a restoration process, where attempts are made to recover an image that has been degraded by using prior knowledge of the degradation process. So Natural Image Denoising is essential process in image processing. Natural images are corrupted by Gaussian Noise and Speckle Noise.

To Removing noise from natural images, Discrete Wavelet Transform(DWT) and Discrete Contourlet Transform(DCT) are used. Recently, researchers have studied the dependency between wavelet coefficients and shrinking them has been shown to be a useful technique for image denoising especially for additive white noise. The Wavelet Denoising scheme thresholds the wavelet coefficients arising from the standard Discrete Wavelet Transform(DWT). Wavelet gives the excellent performance in field of image denoising because of sparcity and multiresolution structure[22]. The main advantages of the discrete wavelet transform over conventional transforms, such as the Fourier transform, are well recognized. Because of its excellent locality in time and frequency domain, wavelet transform is extensively and remarkable used for image processing like compression and denoising. Wavelet transforms have advantages over traditional Fourier Transforms for representing functions that discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic or non-stationary signals. DWT makes the energy of signal concentrate in a small number of coefficients hence the DWT of a noisy image consist of large number of coefficients with low signal to noise ratio (SNR), Removing this low SNR by selecting proper thresholding value [20]. Wavelets are localized in time and frequency whereas the standard Fourier Transform is localized in frequency.

There are several types of wavelets are available such as Orthogonal Wavelets, Biorthogonal Wavelets,with scale function, without scale function and complex wavelets. Haar, Daubechies, Symlets, Coiflets are orthogonal wavelets and Biorthogonal, Reverse Biorthogonal, Meyer Wavelets,Mexican Wavelets are Biorthogonal Wavelets. In this paper, We have taken Daubechies, Biorthogonal, Reverse Biorthogonal Wavelets in Discrete Wavelet Transform.

Biorthogonal wavelet system can be designed to achieve symmetry property and exact reconstruction by using two wavelet filters and two scaling filters instead of one [2,3]. Biorthogonal family contains biorthogonal compactly supported spline wavelets. With these wavelets symmetry and perfect reconstruction is possible using FIR (Finite Impulse Response) filters, which is impossible for the orthogonal filters (except for the Haar filters). The biorthogonal bases uses separate wavelet and scaling functions for the analysis and synthesis of image. Biorthogonal Wavelet Transform:- This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and the other for reconstruction instead of the same single one, interesting properties are derived.We have following biorthogonal wavelet :-
bior1.1 bior1.3 bior1.5 bior2.2 bior2.4 bior2.6 bior2.8 bior3.1 bior3.3 bior3.5 bior3.7 bior3.9 bior4.4 bior5.5 bior6.8. In our proposed work we have used bior6.8 [18]. Daubechies Wavelet transform have the following advantages:-1) It is approximate shift invariant 2) It has perfect reconstruction property. 3) It provides true phase information and no redundancy [24]. The reverse biorthogonal family uses the synthesis functions for the analysis and vice versa.

The Contourlet transform has been developed to overcome the limitations of the wavelets transform [4]. It permits different and elastic number of directions at each scale, while achieving nearly critical sampling.

The Contourlet transform can be worked Firstly, the Laplacian pyramid (LP) is used to decompose the given image into a number of radial subbands, and the directional filter banks (DFB) decompose each LP detail subband into a number of directional subbands. The band pass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combination of the LP and the DFB is a double filter bank named Pyramidal Directional Filter Bank (PDFB), which decomposes images into directional subbands at multiple scales.The combination of the LP and the DFB is a double filter bank named Pyramidal Directional Filter Bank (PDFB), which decomposes images into directional subbands at multiple scales.There are many research works have used CT in different applications, especially in the field of denoising and distortions of the images. Bhateja et al.[12] have presented a Contourlet based speckle reduction method for denoising ultrasound images of breast. In [11], authors proposed a novel method for denoising medical ultrasound images, by considering image noise content as combination of speckle noise and Gaussian noise. Fayed et al.[10] have presented a method for extracting the image features using Contourlet Harris detector that is applied for medical image retrieval. Songet al. [8] have used scale adaptive threshold for medical ultrasound image, wherein the subband Contourlet coefficients of the ultrasound images after logarithmic transform are modeled as generalized Gaussian distribution. Hiremath et al. [7] have proposed a method to determine the number of levels of Laplacian pyramidal decomposition, the number of directional decompositions to perform on each pyramidal level and thresholding schemes which yields optimal despeckling of medical ultrasound images, in particular. This method consists of the log transformed original ultrasound image being subjected to Contourlet transform, to obtain Contourlet coefficients. The transformed image is denoised by applying thresholding techniques on individual band pass sub bands using a Bayes shrinkage rule. The main advantage of contourlet transform over other transforms like curvelets,Contourlet Transform is simple and efficient using iterative filter banks[25].

1.2. Motivation And Justification

In recent years, there are lots of research in image processing. In image processing, image denoising plays a principal role. There are lots of imaging modalities in image denoising. In this paper, we have taken natural images for removing the noise. In Natural images are corrupted by Gaussian Noise, Speckle Noise. To removing these two types of noises, we have used Discrete Wavelet Transform(DWT) and Discrete Contourlet Transform(DCT).

Discrete Cosine Transform and Discrete Fourier Transform could not find out line discontinuity. But Discrete Wavelet Transform could find out line discontinuity. Fourier Transform is useful in non-stationary signals. But Wavelet Transform is used in non-stationary signals as well as stationary signals. Wavelet Transform is well localized in both time and frequency domain. But Fourier transform is only localized in frequency domain. In fourier transform time information is lost. So Fourier Transform cannot be used where both time and frequency information is needed at the same time. Motivating by these facts, Discrete Wavelet Transform is performed well in image denoising.

Comparatively we have used another one Transform is Contourlet Transform. Do and Vetterli have conceived the Contourlet Transform(CT). The main feature of these transform is the potential to efficiently handle 2-D singularities, i.e., edges, unlike wavelets which can deal with point singularities exclusively. Contourlet Transform is advantageous because of its directionality property and anisotropy property. By Motivated all these facts we are inspired to denoise an image in contourlet transform and Wavelet Transform. In this paper, By comparing these two Transforms are Discrete Wavelet Transform(DWT) and Contourlet Transform(CT), and Which one gives best results for natural image denoising.

1.3 Organisation Of The Paper

Section 2 includes Methodology which includes Outline of the Proposed Work, Section 3 includes Experimental Results. Section 4 includes Performance Evaluation Metrics. Ultimately Section 5 includes Conclusion of the paper. Section6 includes References of the paper.

2.METHODOLOGY

2.1.Outline Of The Proposed Method

In this paper, image denoising that apply Discrete Wavelet Transform and Contourlet Transform resides five steps: There are

1. Get the Image as input and adding Gaussian Noise and Speckle Noise

2. Apply Discrete Wavelet Transform(Db-8,Db-16,Bio 6.8,Rbio 5.5) and Contourlet ransform on noisy image and to acquire Noisy Coefficients.

3. Apply Bayes Shrinkage Technique on the modified noisy coefficients.

4. Apply Inverse DWT and Inverse CT on the coefficients to attain denoised image.

5. In our proposed work, To find the best Transformation domain is suitable for bayes shrinkage technique.

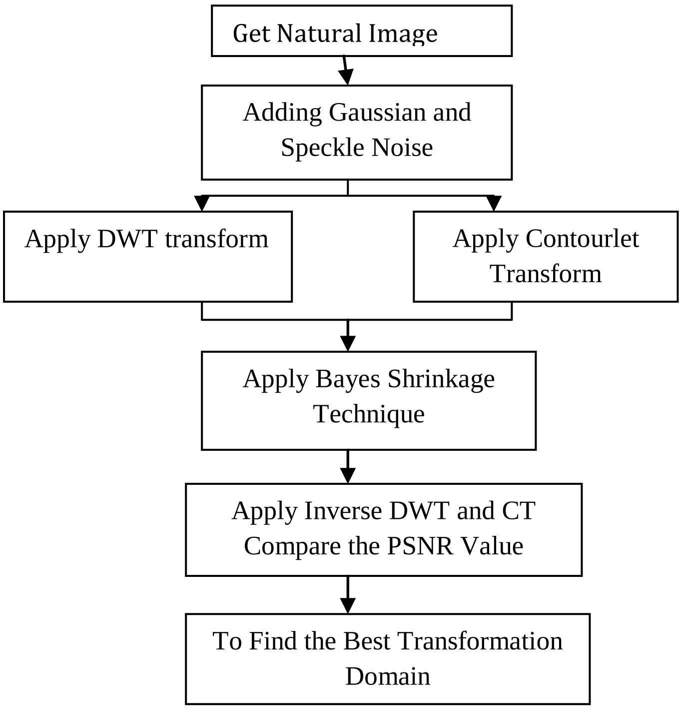


Fig-1: Block Diagram of Discrete Wavelet Transform and Contourlet Transform Using Bayes Shrinkage Technique

2.2. Noises

2.2.1. Gaussian Noise

Gaussian noise is the statistical noise which has its probability density function equal to that of a normal distribution, which is called as the Gaussian distribution. In the different words, the noise values can take on being Gaussian-distributed. It can influence the values of all the pixels[23]. A different case is white Gaussian noise, values at any pair of the times are identically distributed and also statistically independent [21].

$$g(x,y) = f(x,y) + n(x,y) \tag{1}$$

Where is output $g(x,y)$ of original image function $f(x,y)$corrupted by the additive Gaussian Noise Probability density function for Gaussian noise given below

$$p(g) = \sqrt{\frac{1}{2\pi\sigma^2}}\, e^{\frac{-(g-\mu)^2}{2\sigma^2}} \tag{2}$$

Where g represents the grey level, μ the mean value and σ the standard deviation[19].

2.2.2. Speckle Noise

Speckle noise is a multiplicatie noise. Speckle is a complex phenomenon, which degrades image quality with a backscattered wave appearance which originates from many microscopic diffused reflections that passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations [1].

$$g(x,y) = f(x,y) * n(x,y) \tag{3}$$

Where $g(x,y)$is the result of the original image function $f(x,y)$corrupted by the multiplicative noise $n(x,y)$.

2.3. Discrete Wavelet Transform

Discrete Wavelet Transform can offer Multi-resolution analysis and can examine signals in time and frequency domain simultaneously. If any image is decomposed using Wavelet Function then it has two functions: one is Wavelet Function and another one is scaling function. Wavelet Function is used to represent the high frequency component i.e., detail part of an image while scaling function is used to low frequency component i.e., smooth part of an image.[14].

In DWT, the signal is passed through two complimentary filters and emerges two signals, approximation and details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis is called Discrete Wavelet Transform and Inverse Discrete Wavelet Transform. In case of a 2-D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely approximation coefficient LL(low frequency), Detailed coefficient LH(Vertical Details), HL(Horizontal details), HH(Diagonal details) as shown in Fig.2.[6]

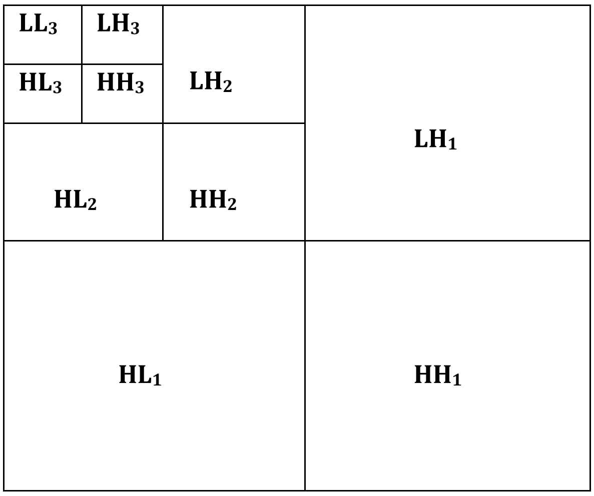


Fig-2: Three Level Decomposition in Discrete Wavelet Transform

1,2,3 – Decomposition Level

H----High Frequency Bands

L-----Low Frequency Bands

2.3.1. Daubechies wavelets

This family is based on orthogonal, and categorized by supported scaling wavelet functions, which generates an orthogonal multi-resolution analysis. This wavelet function is denoted as db1. It is difficult to get an orthogonal supported wavelet that is either symmetric or asymmetric except for Haar wavelets[17]. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. This wavelet has finite vanishing moments. Daubechies wavelets have balanced frequency responses but nonlinear phase responses. Daubechies wavelets are useful in compression and denoising of audio signal processing because of its property of overlapping windows and high frequency coefficient spectrum reflect all high frequency changes. It is easily adapted to soft signals or images, in terms of low frequencies [9][14].

2.3.2. Biorthogonal Wavelets

They are denoted as bior wavelet, biorthogonal if often used instead of orthogonal i.e. rather than having one scaling and wavelet function, there are two scaling functions that may generate different multi-resolution analysis, and accordingly two different wavelet functions used in the analysis and combination [17].

2.3.3. Reverse Biorthogonal

It is based on reconstruction and decomposition of scaling filters. This wavelet has vanishing moments on decomposition for analysis and vanishing moment for the reconstruction of synthesis. It is denoted as rbio [17].

2.4. Contourlet Transform

The contourlet transform is applied for the noisy image to produce decomposed image coefficients. Basically Contourlet transform is a double filter bank structure. It consists of a Laplacian pyramidal filter followed by a directional filter bank .First the Laplacian pyramid (LP) is used to capture the point discontinuities .Then directional filter bank (DFB) used to link point discontinuities into linear structures. Similar to wavelet, contourlet decomposes the image into different scales .Unlike the wavelet ,contourlet decomposes each scale into arbitrarily power of two's number of directions.

The contourlet transformation expression is given by,

$$\lambda^{(t)}_{j,k}(t) = \sum_{i-0}^{3} \Sigma_{n\in z}^{2}\, d_k^{(t)}\left[2n+k_i\right]\left(\Sigma_{m\in z}^{2}\, f_i\left[m\right]_{\phi_3} - 1,2n+m\right) \quad (4)$$

Where , $\lambda_{i,j}^{\omega}(t)$ represents the contourlet transformation of the image. The $d_k^{(l)}$ and $f_i(m)$ represents the directional filter and the band passfilter in the equation. Thus j, k and n represent the scale direction and location. Therefore l represents the number of directional filter bank decomposition levels at different scales j. Thus the output of contourlet transform is a decomposed image coefficients.[13]

2.5. Threshold Shrinkage Technique

2.5.1. Bayes Shrink

Bayes Shrink was proposed in[5]. As noise is additive in nature so noisy image is additive sum of original image and noise, in terms of variance it can be stated that

$$\hat{\sigma}_y^2 = \hat{\sigma}_x^2 + \hat{\sigma}_n^2 \quad (5)$$

Where $\hat{\sigma}_y^2$ is variance of noisy image $\hat{\sigma}_x^2$ is variance of original image and $\hat{\sigma}_n^2$ is variance of noise. A good estimated threshold is Bayesian Threshold t_B is defined as

$$t_B = \frac{\partial_n^2}{\partial_x} \quad (6)$$

Where $\hat{\sigma}_x$ is obtained from the following equation

$$\hat{\sigma}_x = \sqrt{\max\left(\hat{\sigma}_y^2 - \hat{\sigma}_n^2, 0\right)} \quad (7)$$

In Bayes Shrink, thresholding is done at each subband in the wavelet decomposition which improves outcome and also completely denoise the flat regions of the image. But it is less sensitive to the noise around edges[5][15].

3. EXPERIMENTAL RESULTS

Experiments were performed to denoising a Natural images Lena, Barbara,Peppers, Cameraman original images shown in Fig.3. To denoise the natural images with different wavelet bases such as Daubechies, Biorthogonal, Reverse Biorthogonal using Gaussian and Speckle Noise is shown in Fig 4. Reverse BiOrthogonal gives better results other Wavelet base. So, Revserse Biorthogonal with different noise variance is applied for Gaussian & Speckle Noise that is shown in Fig.5. To Compare the Contourlet Transform with the same images using different noise variance is shown in Fig.6.

(a) (b)

(c) (d)

Fig-3: Original Images (a) Lena Image, (b) Cameraman Image, (c)Peppers Image, (d) Barbara Image

Bayes Shrink		**Gaussian Noise**	**Speckle Noise**
Noisy Image			
Denoised Images Using Different Wavelet Bases	Db-8		
	Db-16		
	Biorthogonal		
	Reverse Biorthogonal		

Fig-4(a): Lena Image with different wavelet bases using Speckle & Gaussian Noise

Bayes Shrink		**Gaussian Noise**	**Speckle Noise**
Noisy Image			
Denoised Images Using Different Wavelet Bases	Db-8		
	Db-16		
	Biorthogonal		
	Reverse Biorthogonal		

Fig-4(b): Cameraman Image with different wavelet bases using Speckle & Gaussian Noise

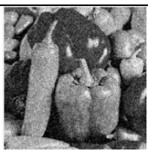
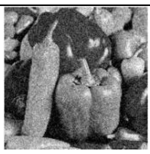
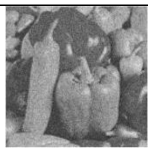
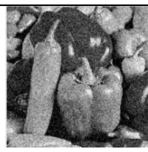
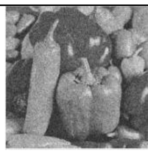
Bayes Shrink		**Gaussian Noise**	**Speckle Noise**
Noisy Image			
Denoised Images Using Different Wavelet Bases	Db-8		
	Db-16		
	Biorthogonal		
	Reverse Biorthogonal		

Fig-4(c): Peppers Image with different wavelet bases using Speckle & Gaussian Noise

Bayes Shrink		**Gaussian Noise**	**Speckle Noise**
Noisy Image			
Denoised Images Using Different Wavelet Bases	Db-8		
	Db-16		
	Biorthogonal		
	Reverse Biorthogonal		

Fig-4(d): Barbara Image with different wavelet bases using Speckle & Gaussian Noise

Natural Image	**Noisy Variance**	**Speckle Noisy Image**	**Speckle Denoised image**
Lena (Lena.jpg)	0.01		
	0.02		
	0.03		
Camera Man(camera Man.jpg)	0.01		
	0.02		
	0.03		

Fig-5(a): Lena & Cameraman Image with Reverse biorthogonal wavelet base using Gaussian Noise

Natural Image	**Noisy Variance**	**Speckle Noisy Image**	**Speckle Denoised image**
Lena (Lena.jpg)	0.01		
	0.02		
	0.03		
Camera Man(camera Man.jpg)	0.01		
	0.02		
	0.03		

Fig-5(b): Lena & Cameraman Image with Reverse biorthogonal wavelet base using speckle noise

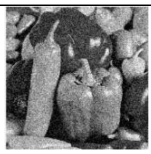
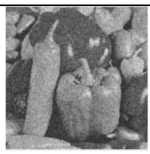
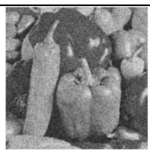
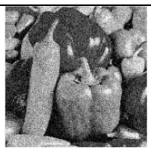
Natural Image	Noise Variance	Gaussian Noisy Image	Gaussian Denoised Image
Peppers (peppers.jpg)	0.01		
	0.02		
	0.03		
Barbara (Barbara.jpg)	0.01		
	0.02		
	0.03		

Fig-5(c): Peppers & Barbara Image with Reverse biorthogonal wavelet base using Gaussian Noise

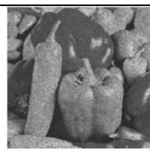
Natural Image	Noise Variance	Speckle Noisy Image	Speckle Denoised Image
Peppers (peppers.jpg)	0.01		
	0.02		
	0.03		
Barbara (Barbara.jpg)	0.01		
	0.02		
	0.03		

Fig-5(d): Peppers & Barbara Image with Reverse biorthogonal wavelet base using Speckle Noise

Natural Image	**Noisy Variance**	**Gaussian Noisy Image**	**Gaussian Denoised image**
Lena (Lena.jpg)	0.01		
	0.02		
	0.03		
Camera Man(camera Man.jpg)	0.01		
	0.02		
	0.03		

Fig -6(a): Lena & Cameraman Image with Contourlet base using Gaussian Noise

Natural Image	**Noisy Variance**	**Speckle Noisy Image**	**Speckle Denoised image**
Lena (Lena.jpg)	0.01		
	0.02		
	0.03		
Camera Man(camera Man.jpg)	0.01		
	0.02		
	0.03		

Fig -6(b): Lena & Cameraman Image with Contourlet base using Speckle Noise

Natural Image	**Noisy Variance**	**Gaussian Noisy Image**	**Gaussian Denoised image**
Peppers (peppers. jpg)	0.01		
	0.02		
	0.03		
Barbara (barbara.jpg)	0.01		
	0.02		
	0.03		

Fig-6(c): Peppers & Barbara Image with Contourlet base using Gaussian Noise

Natural Image	**Noisy Variance**	**Speckle Noisy Image**	**Speckle Denoised image**
Peppers (peppers. jpg)	0.01		
	0.02		
	0.03		
Barbara (barbara.jpg)	0.01		
	0.02		
	0.03		

Fig-6(d): Peppers & Barbara Image with Contourlet base using speckle Noise

4. PERFORMANCE EVALUATION

4.1.1. Peak- Signal to Noise-Ratio(PSNR)

It gives the ratio between possible power of a signal and the power of corrupting noise present in the image[26].

$$PSNR = 20\log 10(255/RMSE) \quad (8)$$

Higher the PSNR gives lower the noise in the image i.e.,higher the image quality.

4.2. Performance Evaluation

The performance of Wavelet and Contourlet Transform in Bayes Shrinkage Technique were examined using the PSNR Value. The First experiment in conducted to estimate the performance different wavelet families such as Daubechies-8,16, Biorthogonal, Reverse Biorthogonal. The Results are shown in Table.1. Reverse Biorthogonal gives the better results. So, We apply various noise variance in Reverse Biorthogonal and and the results are shown in Table.2. The Second Experiment is performed using Contourlet Transform with different noise variance and the result are shown in Table.3.

Table -1: Different Wavelet Bases with Speckle & Gaussian Noise in Natural Images

Natural Image	Wavelet Bases	Gaussian Noise PSNR	Speckle Noise PSNR
Lena (Lena.jppg)	DB-8	19.21	20.0938
	DB-16	19.0324	19.8987
	Biorthogonal	18.9821	19.5765
	Reverse Biorthogonal	23.025	25.2657
Camera Man (cameraman.jpg)	DB-8	21.120	22.3415
	DB-16	20.9146	22.0752
	Biorthogonal	20.8122	21.2149
	Reverse Biorthogonal	21.2981	22.5069
Peppers (peppers.jpg)	DB-8	19.0165	19.6862
	DB-16	18.8824	19.5046
	Biorthogonal	18.9947	19.6652
	Reverse Biorthogonal	23.1982	25.3233
Barbara (Barbara.jpg)	DB-8	18.9717	19.8719
	DB-16	18.8596	19.7373
	Biorthogonal	18.9618	19.8004
	Reverse Biorthogonal	22.1769	24.0758

Table -2: Reverse Biorthogonal with noise variances in Gaussian & Speckle Noise

Natural Image	Noise Variance	Gaussian Noise PSNR	Speckle Noise PSNR
Lena (Lena.jpg)	0.01	23.0303	25.2403
	0.02	23.0522	24.297
	0.03	23.0078	23.6064
CameraMan (cameraman. Jpg)	0.01	21.2084	22.5102
	0.02	21.1622	21.9428
	0.03	21.1441	21.4312
Peppers (peppers.jpg)	0.01	23.159	25.3398
	0.02	23.132	24.4619
	0.03	23.1415	23.8241
Barbara (Barbara. jpg)	0.01	22.1781	24.0834
	0.02	22.2267	23.4768
	0.03	22.1944	22.8951

Table-3: Contourlet Base with Speckle & Gaussian Noise in Natural Images

Natural Image	Noise Variance	Gaussian Noise PSNR	Speckle Noise PSNR
Lena (Lena.jpg)	0.01	20.0365	25.7485
	0.02	19.8969	22.8193
	0.03	19.6893	21.0411
CameraMan (cameraman. Jpg)	0.01	20.2188	25.636
	0.02	20.08	22.6343
	0.03	19.7697	20.8933
Peppers (peppers.jpg)	0.01	20.1504	26.6008
	0.02	20.029	23.6379
	0.03	19.7254	21.9381
Barbara (Barbara. jpg)	0.01	20.0497	25.887
	0.02	19.9449	22.9532
	0.03	19.7298	21.2659

From Table 1 it is noted that the wavelet families is best fit for speckle noise removal than Gaussian Noise. All type of wavelet bases are equally perform well in removing speckle and Gaussian Noise. It is observed that the Performance of Reverse Biorthogonal wavelet base is somewhat better than other bases. So Reverse Biorthogonal with various noise variance is applied and the results are shown in Table 2. To Compare Contourlet Base using Gaussian & Speckle Noise with different noise variance. In Contourlet Transform, Speckle Noise gives best result than Gaussian noise and it is shown in Table 3.

5. CONCLUSION

Experiments were performed to analyse the best suitable wavelet bases such as Daubechies(Db-8,Db-16), Biorthogonal, Reverse Biorthogonal. In Wavelet Bases, Reverse Biorthogonal gives best results than other bases. So we apply different images, different noises , different noise variances, in Reverse Biorthogonal. By comparing contourlet base, we apply the same images, same noises and same noise variances are used. In this paper presents a comparative Study on Natural Image Denoising Using Discrete Wavelet Transform(DWT) and Contourlet Transform with Bayes Shrinkage Technique.

The Peak-Signal to Noise-Ratio(PSNR) value is used to find out the best transformation domain in image denoising. Finally, we conclude that the Discrete Wavelet Transform is best for Gaussian Noise and Contourlet Transform is best for Speckle Noise.

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