Empirical Evaluation of Shrinkage Thresholding Technique in Contourlet Domain

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Abstract*- Medical imaging emanate as one of the most preeminent sub-fileds in the world of science and technology. Image Denoising is one of the primary step in digital image processing. The cardinal intention is to eliminate the noise from the input image. Medical image is used as input image. Medical images are obstructed by a variety of noises depending on their devices through acquisition and transmission & Storage. In this for denoising, Gaussian noise, Speckle noise, and Salt and Pepper noise in Magnetic Resonance Image (MRI) undergo a contourlet domain for decomposition of input images. Contourlet transform is used to preserve the edges and contours the regions. After decomposition some thresholding methods are used, they are Heursure shrink, Min-Max shrink, Neighsure shrink, Bishrink, Visu shrink, sure shrink, Neigh shrink, Bayes shrink, Normal shrink, Block shrink. Thresholding function is used to identify and filter the noisy coefficient and take inverse transform to intermittent the original image. Theresholding techniques are instigate and scrutinise its performance to find the best result. MRI images are taken as datasets for quantitative validation. The Peak Signal-to-Noise Ratio (PSNR), weighted signal-to-noise ratio (WSNR), visual signal-to-noise ratio (VSNR) are employed to quantify the performance of denoising.

Keywords--Image Denoising, Contourlet, MRI Image, PSNR, WSNR, VSNR,Threshold.

I. INTRODUCTION

Digital image processing is used widely in many crucial fields such as medical imaging for diagnosis of diseases, face recognition for security purposes and so on. Image Denoising is a central pre-processing step in image processing to unfasten the noise in order to strengthen and recover small details that may be hidden in the data. The goal of denoising is to detach the noise, which may corrupt an image during its acquisition or transmission, while retaining its quality.

Medical images are received from medical devices such as X-Ray, Computed Tomography (CT), Positron Emission Tomography (PET), Single Positron Emission Tomography (SPET) and Magnetic Resonance Image (MRI). MRI is as for examining soft tissues, showing inflammation and creating cross-sectional pictures, organs, and bones. In this work different types of noises are used some of them are Gaussian noise, Speckle noise, and Salt and Pepper noise. Speckle noise is also known as multiplicative noise. It is similar to phasors with random amplitude and phase in free space. Speckle noise can be treated as infinite sum of independents. Impulse noise results in dark pixels in bright regions and bright pixels in dark regions. Impulse noise is known as salt and pepper noise. Impulse noise is mainly caused during analog to digital preprocessing, compressing of images and videos, transmission of signals and acquisition of signals. Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. The DWT analysis problems have been solved by the Contourlet Transform (CT) which can efficiently approximate a smooth contour at multiple resolutions. So, here, Contourlet Transform is used. Thresholding is one of the essential technique in image processing techniques such as Bayes Shrink, Visu Shrink, Neigh Shrink, Sure Shrink, Neighsure Shrink, Normal Shrink, and Block Shrink, Min-Max Shrink and Bivariate Shrink and, Normal shrink. These methods are used to make a noise free in an image.

A. Related Work

Medical images are typically corrupted with noise, which hinder the medical diagnosis based on these images. There has been substantial interest in the problem of denoising of images in general. Tools from traditional image processing field have been applied to denoised MR images [36].

Image De-noising is used to produce good estimates of the original image from noisy observations. The recovered image should contain less noise than the observations while still keep sharp transitions (i.e edges) [8]. Image de-noising techniques vary from simple thresholding to complicate model based algorithm. However simple thresholding methods can remove most of the noise.

Denoising is nothing but the removing noise from image while retaining the original quality of the image. The great challenge of image denoising is how to preserve the edges and all fine details of an image while suppression of noise. It still remains challenge for researchers as noise removal introduces artifacts and causes blurring of the images [9]. So, it is necessary to develop an efficient denoising technique to avoid such knowledge corruption.

During acquisition or transmission MRI images are largely corrupted by noise. Also, noise is also made as a result of imperfect instrument used during processing, interference and compression. In the digital images like MRI, noise are low as well as high frequency components. Removing high frequency components is very easy as comparatively with low frequency components as real signal and low frequency noise cannot be distinguished easily [19]. Image noise can be defined as random variation of brightness or color information image produced by the sensor and circuitry of the scanner. Noise in MRI poses a lot of problem to medical personnel by interfering with interpretation of MRI for diagnosis and treatment of human .Image noise in large measures contributes high hazards faced by human [12]. Noise in MRI mostly obeys Rician distribution. The term rician noise is used to the error between underlying image intensities and the observed data. As it has non zero mean, its mean depends on the local intensity in the image. Also, rician noise is signal dependent and particularly problematic in high resolution, low signal to noise ratio regime where it not only causes random fluctuations but also introduces as signal dependent bias to the data that reduces image contrast. As bias field signal is low frequency signal which corrupts MRI images because in homogenities in the magnetic field of MRI machines. It blurs the images and reduces the high frequency content of image such as edge, contours and also alters the intensity values of image pixels. Because of this tissues have different grey level distribution across image. Image processing algorithm like segmentation, classification or texture analysis use the grey level values of that image pixels which will not give satisfactory result. The preprocessing is required for correction of bias field signal before submitting corrupted MRI to such algorithm [20]. Rician noise affects the image in both quantitative and qualitative manner and thus it hinders image analysis, interpretation and feature detection [20]. So denoising method is required which removes this noise.

Gaussian noise is statistical noise having a Probability Density Function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution[10].This noise model is additive in nature [6]. Additive white Gaussian noise (AWGN) can be caused by poor quality image acquisition, noisy environment or internal noise in communication channels.

Speckle-noise is a granular noise degrades the quality of the active radar, synthetic aperture radar (SAR), and medical ultrasound images. Speckle noise occurs in conventional radar due to random fluctuations in the return signal from an object [16].

Salt & pepper noise model, there is only two possible values a and b. The probability of getting each of them is less than 0.1 (else, the noise would greatly dominate the image). For 8 bit/pixel image, the intensity value for pepper noise typically found nearer to 0 and for salt noise it is near to 255. Salt and pepper noise is a generalized form of noise typically seen in images [37]. In image criteria the noise itself represents as randomly occurring white and black pixels. Salt and pepper noise occurs in images under situations where quick transients, such as faulty switching take place. This type of noise can be caused by malfunctioning of analog-to-digital converter in cameras, bit errors in transmission, etc.

The Contourlet transform has been developed to overcome the limitations of the wavelets transform [28]. 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 [5]. Have presented a Contourlet based speckle reduction method for denoising ultrasound images of breast. In [17], authors proposed a novel method for denoising medical ultrasound images, by considering image noise content as combination of speckle noise and Gaussian noise [13]. The method for extracting the image features using Contourlet Harris detector that is applied for medical image retrieval [22]. This is used to 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 [18]. The proposed method is 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 threshold method, developed by Donoho [34] in 1995, provides a viable treatment option for the wavelet coefficients of nonlinear processing and, consequently, significantly advanced the field of image denoising. Bayes shrink was proposed by Chang, Yu and Vetterli [29]. The objective of this technique is to minimalize the Bayesian risk, and therefore named as Bayes Shrink. It uses soft thresholding and is subband-dependent, which meant that thresholding in the wavelet decomposition is done at each subband of resolution. This shrinkage technique includes the use of neighboring coefficients. The window sizes used for the neighborhood window could vary being 3X3, 5X5, 7X7, 9X9, etc. amongst them 3X3 serves the best [31]. The threshold value calculated using universal shrinkage technique but since this does not provide an optimal output.

Block Shrink is a completely data-driven block thresholding approach and is also easy to implement [23]. It can decide the optimal block size and threshold for every wavelet sub band by minimizing Stein’s unbiased risk estimate (SURE).

Sure Shrink threshold was developed by Donoho and Johnston [34], [35]. For each sub-band, the threshold is determined by minimizing Stein's Unbiased Risk Estimate (SURE) for those coefficients.

Visu Shrink thresholding is done by applying universal threshold proposed in [32]. It uses the hard thresholding rule. Threshold value t is directly proportional to the noise’s standard deviation. With additive Gaussian noise assumption Visu Shrink exhibits better denoising performance than the universal threshold but Visu Shrink does not deal with minimizing the mean squared error.

Neigh Shrink [26], for each noisy wavelet coefficient to be shrinked, a square neighboring window centered at it. In sub band thresholding, the threshold and neighboring window size keep unchanged in all sub bands. Neigh Shrink Sure [25] is an improvement over Neigh Shrink [26], which has disadvantage of using a non-optimal universal threshold value and the same neighboring window size in all wavelet subbands NeighShrink Sure. It can determine an optimal thresholdand neighboring window size for every subband by the Stein’s unbiased risk estimate (SURE) [25]. They combine the unknown noiseless coefficients from sub bands into the corresponding 1-D vector. As using stein's approach for almost any fixed estimator based on the data, the expected loss (i.e. risk) can be estimated in an unbiased way.

Heursure Thresholding is a mixed rule. It is a mixture of the two previous rules: Rigrsure and universal threshold [30].

Bivariate shrinkage function which depends on both coefficient and its parent yield improved results for wavelet based image denoising. Here, we modify the Bayesian estimation problem as to take into account the statistical dependency between a coefficient and its parent [15].

Min-Max Shrink (MS) the threshold value is calculated using Min-Max principle. The Min-Max estimator is the one that realizes the minimum of the maximum MSE obtained for the cost function [14].

Normal shrink method is computationally more efficient and adaptive because the parameters required for estimating the threshold depends on subband data. Performance of Normal shrink is similar to Bayes shrink. But normal shrink preserves edges better than Bayes shrink [14].

B. Motivation and justification of the proposed work

Image Denoising is the superior roal in image processing.Denoising is nothing but it detach the noise from image while retaining the original quality of the image. The Contourlet transform (CT) is better than Discrete Wavelet transform (DWT) because it produce decomposed image coefficients Wavelet transform gives frequency representation of raw signal at any given interval of time. The disadvantage of wavelet transform is to consider small coefficients are likely due to noise and large coefficient are likely due to important signal features. The DWT is used to find line discontinuity. It can’t preserve edges, curves and some details. So, there is a need of contourlet transform (CT). In this CT is used to contour the regions. The main advantage of contourlet transform is that it has a double filter bank structure. It consists of a Laplacian pyramidal filter and a directional filter bank. The Laplacian pyramid (LP) is used to capture the point discontinuities. The directional filter bank (DFB) is used to link point discontinuities into linear structures. In this paper for denoising Contourlet transform based thresholding techniques is used for image denoising.

C. Organization of the Work

The rest of the paper is organized as follows. The methodologies are discussed in section II. Experimental results are shown in section III. Performance Evaluation is discussed in section IV. Finally conclusion is presented in section V.

II. METHODOLOGY

A. Outline of the Work

In this work denoising is performed by Contourlet Transform and Threshold Shrinkages. The system is expressed in Figure 1 The input image is taken and then the noise is added in the image. Contourlet transform

(CT) is applied to noisy image. Next apply several thresholding methods on the transformed image. The applied thresholding methode are namely, Heursure shrink, Min-Max shrink, Neighsure shrink, Bishrink, Visu shrink, sure shrink, Neigh shrink, Bayes shrink, Normal shrink, Block shrink. Finally, Inverse Contourlet Transform (ICT) is applied to get the denoised image.

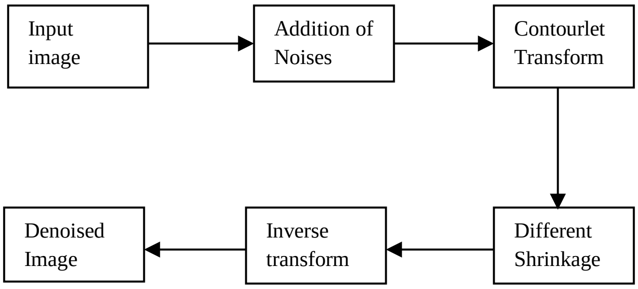


Figure.1 Block Diagram Of Image Denoising Using Contourlet Transform

B. *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 2's number of directions. The contourlet transformation expression is given by,

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

where, $\lambda^{\omega}_{i,j}(t)$ represents the contourlet transformation of the image. The $dk^{(l)}$ and $f_i(m)$ represents the directional filter and the band pass filter 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 [4].

C. *Different Types of Noise*

In this different types of noise like Gaussian noise, Speckle noise, Salt and pepper noise.

1. *Gaussian Noise*

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. A special case is white Gaussian noise, in which the values at any pairs of times are statistically independent (and uncorrelated). In applications, Gaussian noise is most commonly used as additive white noise to yield additive white Gaussian noise. The probability density function of n-dimensional Gaussian noise is,

$$f(x) = \left((2\pi)^n \det K\right)^{-1/2} \exp\left(-(x-\mu)^T K^{-1}(x-\mu)\right)/2 \qquad (2)$$

where x is a length-n vector, K is the n-by-n covariance matrix, μ is the mean value vector, and the superscript T indicates matrix transpose.[4]

2. *Speckle Noise*

Speckle noise is multiplicative noise unlike the Gaussian and salt pepper noise. This noise can be modeled by random vale multiplications with pixel values of the image and can be expressed as

$$P = I + n * I \qquad (3)$$

where, P is the speckle noise distribution image, I is the input image and n is the uniform noise image by mean o and variance v.[1]

3. *Salt and Pepper Noise*

Salt and pepper noise is an impulse type of noise. It is actually the intensity spikes. This type of noise is coming due to errors in data transmission. This noise occurs in the image because of sharp and sudden changes of image signal. For images corrupted by salt and pepper noisethe noisy pixels can take only the maximum and the minimum values in the dynamic range. It is found that an 8-bit image, the typical value for pepper noise is 0 and for salt noise it is 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations or timing errors in the digitization process [1].

$$p(z)=\begin{cases} p_a & \text{for } z=a \\ p_b & \text{for } z=b \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

D. Different Thresholding Techniques

In this different types of thresholding like Heursure shrink, Min-Max shrink, Neighsure shrink, Bishrink, Visu shrink, sure shrink, Neigh shrink, Bayes shrink, Normal shrink, Block shrink.

1. Visu Shrink

Visu shrink is a hard threshold method. The threshold value 't' here is in proportion with the standard deviation of the noise [21]. Visu Shrink does not deal with minimizing the mean squared error. It can be viewed as general-purpose threshold selectors that exhibit near optimal min-max error properties and ensures with high probability that the estimates are as smooth as the true underlying functions. Visu Shrink follows the global thresholding scheme where there is a single value of threshold applied globally to all the wavelet coefficients. The formula for calculating the threshold value is: [34]

$$T = \sigma\sqrt{2\log M} \qquad (5)$$

where,

$\sigma = \text{Noise Variance}$

$M = \text{Image length}$

$$\sigma = \frac{median\{|W_k| : k = 1,2,\ldots n\}}{0.6745}$$

W_k=Detail coefficients at the finest level

2. Block Shrink

Block Shrink is a completely data-driven block thresholding approach and is also easy to implement [23]. It can decide the optimal block size and threshold for every wavelet subband by minimizing Stein's unbiased risk estimate (SURE). It also limits the block size search range by following [23].

$$1 \le L \le \left\lceil \left(N/2^k\right)^{3/4} \right\rceil \qquad (6)$$

3. *Bayes Shrink*

Bayes Shrink is a sub band adaptive data driven thresholding method. This method assumes that the coefficients are distributed as a generalized Gaussian distribution in each sub . Bayes Shrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [29]. The Bayes threshold is defined as

$$\lambda = \frac{\sigma^2_{noise}}{\sqrt{\max\left(\sigma^2_y - \sigma^2_{noise}, 0\right)}} \qquad (7)$$

This method defines the rules for applying the threshold to the coefficients. The threshold is compared to all coefficients of the contourlet domain and when the coefficients are less than the threshold value they are assigned zero values, otherwise they are kept unaltered. The reason behind it is that small coefficients are supposed to be not of signal elements and so can be modified to zeroes. The large coefficients are supposed to be of important signal features band. It also finds a threshold which minimizes the Bayesian risk.σ^2 is the noise variance and σ is the signal variance.

4. Heursure Thresholding

Mixed rule is a mixture of the two previous rules: Rigrsure and universal threshold. First step calculates the variables A and B according to the system of Eq. (4)

$$\begin{cases} A = \dfrac{\sum_{i=1}^{n} |X|^2 - n}{n} \\ B = \sqrt{\dfrac{1}{n}} \left[\dfrac{\log n}{\log 2} \right]^3 \end{cases} \tag{8}$$

If A is less than B the universal form threshold is as Eq. (3) is used, else threshold selection rule based on Rigrsure is adopted. A and B are defined by [30].

5. Min max Shrink

A fixed threshold selected to obtain minimum of maximum performance for mean square error against an ideal procedure. The min max principle is used in statistics in order to find a good estimator. The algorithm of the threshold selection is [2] :

$$T = 0.3936 + 0.1829 \frac{\log n}{\log 2} \tag{9}$$

6. Neigh Shrink

The method Neigh Shrink thresholds the coefficients according to the magnitude of the squared sum of all the coefficients, i.e., the local energy, within the neighborhood window [3]. The neighborhood window size may be 3×3, 5×5, 7×7, 9×9, etc. But, the authors have already demonstrated through the results that the 3×3 window is the best among all window sizes. The neighboring window of size 3* 3 centered at the coefficient to be shrinked. The shrinkage function for Neigh Shrink of any arbitrary 3×3 window centered at (i,j) is expressed as:

$$T_{ij} = 1 - \frac{T_u^2}{S_{ij}^2} \tag{10}$$

where, T_u^2 the universal threshold and S_{ij}^2 is the squared sum of all wavelet coefficients in the respective 3×3 window given by:

$$S_{ij}^2 = \sum_{n=j-1}^{j+1} \sum_{m=i-1}^{i+1} Y_{m,n}^2 \tag{11}$$

7. Sure Shrink

This Sure Shrink threshold was developed by Donoho and Johnston [34], [35]. For each sub-band, the threshold is determined by minimizing Stein's Unbiased Risk Estimat (SURE) for those coefficients. Sure is a method for estimating the loss $(\mu'-\mu)^2$ k in an unbiased fashion, where μ' is the estimated mean and μ is the real mean. The threshold is calculated as follows:

$$t^* = \min\left(t, \sigma\sqrt{2\log 2n}\right) \tag{12}$$

Where,

σ =Standard deviation of noise

n= number of pixel elements in the image

Donoho and Johnsto [34] pointed out that Sure Shrink is automatically smoothness adaptive. This implies that the reconstruction is smooth wherever the function is smooth and it jumps wherever there is a jump or discontinuity in the function [33]. This method can generate very sparse wavelet coefficients resulting in an inadequate threshold.

8. Normal Shrink

The optimum threshold value for Normal Shrink or Norm Shrink is given by [27], [7]:

$$T_{NORM} = \frac{\lambda \sigma_v^2}{\sigma_y^2} \tag{13}$$

Where, the parameter λ is given by the following equation:

$$\lambda = \sqrt{\log\left(\frac{L_k}{J}\right)} \tag{14}$$

Lk is the length of the sub-band at kth scale. And, J is the total number of decomposition. σ_v is the estimated noise variance, and σ_y is the standard deviation of the subband of noisy image. Normal Shrink also performs soft thresholding with the data driven subband dependent threshold TNORM, which is calculated by the equation (13).

9. Neighsure shrink

Neigh ShrinkSURE, an image denoising method proposed in [24] is an improved version of Neigh Shrink. The Neigh Shrink uses a suboptimal universal threshold and identical window size in all wavelet subbands, whereas the improved version of it determines an optimal threshold and neighboring window size for every subband by the Stein's unbiased risk estimate (SURE) as given in (15).

$$\left(T^s, K^s\right) = \arg\min_{T,K} SURE\left(w_s, T, K\right) \tag{15}$$

Where T is the threshold, k is the window size and s denotes the subband.

10. Bi shrink

To model the statistics of wavelet coefficients of images, a new simple non-Gaussian bivariate probability distribution function is implemented in this paper. The model captures the dependence between a wavelet coefficient and its parent. Using Bayesian estimation theory, this model is derived, which generalizes the soft thresholding approach. The new shrinkage function, which depends on both the coefficient and its parent, yields improved results for wavelet based image denoising.

Let w2 represent the parent of w1. Then, y = w+n. Where w = (w1, w2), y = (y1, y2) and n = (n1, n2). The noise values n1,n2 are zero mean Gaussian. Based on the empirical histograms, the non Gaussian bivariate PDF is given by,

$$p_w(w) = \frac{3}{2\pi\pi^2} \exp\left(-\frac{\sqrt{3}}{\sigma}\sqrt{w_1^2 + w_2^2}\right) \tag{16}$$

With this PDF, w1and w2 are uncorrelated, but not independent. The MAP estimator of w1 yields the following bivariate shrinkage function.

$$\hat{w}_1 = \frac{\sqrt{y_1^2 + y_2^2} - \frac{\sqrt{3}\sigma_n^2}{\sigma}}{\sqrt{y_1^2 + y_2^2}} y_1 \tag{17}$$

For this bivariate shrinkage function, the smaller the parent value, the greater the shrinkage. This is consistent with other models, but here it is derived using a Bayesian estimation approach beginning with the new bivariate non-Gaussian model [11].

III. EXPERIMENTAL RESULTS

Experiments were conducted to denoise a MRI image of a neck which is an original image shown in Figure 2. Gaussian noise, Speckle noise, and Salt and Pepper noises were considered. The denoised output images for different Thresholding and different noises is presented in Figure 3.

Figure 2. Original Image

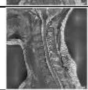
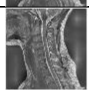
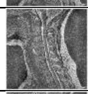
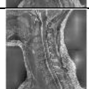
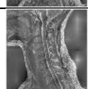
Threshold	Gaussian Noise	Speckle Noise	Salt & Pepper Noise
Noisy Image			
Heursure shrink			
Min-Max shrink			
Neighsure shrink			
Bishrink			
Visu shrink			
Sure shrink			
Neigh Shrink			
Bayes shrink			
Normal shrink			
Block shrink			

Figure 3. Denoised PSNR using different Thresholding and different noise

IV. PERFORMANCE ANALYSIS

A. Performance Metrics

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

PSNR is the peak signal to noise ratio in decibles (DB). The PSNR is measured in terms of bits per sample or bits per pixel. The image with 8 bits per pixel contains from 0 to 255. The greater PSNR value is, the better the image quality and noise suppression.

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{peak}^2}{\mathrm{MSE}}\right) \tag{18}$$

2. *Weighted Signal- to -Noise Ratio (WSNR)*

Weighted SNR (WSNR) for the subjective quality measure of halftone image. WSNR weights the Signal-to-Noise Ratio (SNR) according to the contrast sensitivity function (CSF) of the human visual system. For an image of size M×N pixels, WSNR is defined as

$$\mathrm{WSNR}(\mathrm{dB}) = 10\log_{10}\left(\frac{\Sigma_{u,v}\left|X(u,v)C(u,v)\right|^2}{\Sigma_{u,v}\left|X(u,v-Y(u,v)C(u,v))\right|^2}\right) \tag{19}$$

3. *Visual Signal- to- Noise Ratio (VSNR)*

The VSNR, in decibels, is accordingly given by

$$\mathrm{VSNR} = 10\log_{10}\left(\frac{C^2(I)}{VD^2}\right) \tag{20}$$

B. *Performance Evaluation*

The performance of the Contourlet transform and different Thresholding techniques were studied using the metrics PSNR, WSNR, VSNR. The first experiment is conducted to estimate the performance of denoised image for PSNR and different threholding techniques & different noises. Results are shown in Table I. The second experiment is conducted to estimate the performance of denoised image WSNR and different threholding techniques & different noises. Results are shown in Table II. The third experiment is conducted to estimate the performance of denoised image VSNR and different threholding techniques & different noises. Results are shown in Table III. Finally, conclude the performance of best Thresholding method and related metrics.

TABLE I. DENOISED PSNR WITH DIFFERENT THRESHOLD AND DIFFERENT NOISE

Threshold	**Denoised image PSNR**		
	Gaussian Noise	***Speckle Noise***	***Salt & Pepper Noise***
Heursure shrink	28.0694	30.5124	17.206
Min-Max shrink	27.8145	33.4479	17.3634
Neighsure shrink	26.9722	30.3789	17.2075
Bishrink	21.1517	29.8754	24.0373
Visu shrink	27.5561	30.9251	19.9888
Sure shrink	27.2621	24.2536	24.2536
Neigh Shrink	28.2745	31.2088	17.1714
Bayes shrink	28.0186	30.4604	17.1451
Normal shrink	27.7536	30.9245	17.1828
Block shrink	20.6996	29.641	24.324

TABLE II. DENOISED WSNR WITH DIFFERENT THRESHOLD AND DIFFERENT NOISE

Threshold	**Denoised image WSNR**		
	Gaussian Noise	***Speckle Noise***	***Salt & Pepper Noise***
Heursure shrink	29.4174	34.3102	21.2778
Min-Max shrink	27.4546	34.3225	21.6871
Neighsure shrink	29.6736	34.1976	21.3786
Bishrink	25.4034	33.8573	28.0604
Visu shrink	28.1057	29.9753	22.7942
Sure shrink	29.1068	28.3104	28.3104
Neigh Shrink	29.721	34.5057	21.3194
Bayes shrink	29.5975	34.3088	21.2195
Normal shrink	29.6331	34.5468	21.2458
Block shrink	19.6554	30.7865	22.5432

TABLE III. DENOISED VSNR WITH DIFFERENT THRESHOLD AND DIFFERENT NOISE

Threshold	**Denoised image VSNR**		
	Gaussian Noise	***Speckle Noise***	***Salt & Pepper Noise***
Heursure shrink	27.5682	41.1645	10.2994
Min-Max shrink	27.4655	40.742	10.5432
Neighsure shrink	30.5342	40.9184	10.3031
Bishrink	28.273	40.4929	17.0016
Visu shrink	27.1584	35.5831	15.7637
Sure shrink	29.8213	17.2712	17.2712
Neigh Shrink	28.3712	41.4075	10.3122
Bayes shrink	28.0851	40.8037	10.3094
Normal shrink	29.2415	41.0137	10.3006
Block shrink	25.6783	33.4567	17.1789

V. CONCLUSION

In this paper, the image de-noising using Contourlet transform with different thresholding techniques are used to improve the quality of medical images. Mainly in the case of presence of Speckle noise, Salt and Pepper noise, and Gaussian noise, thresholding techniques are very much required to improve the medical image diagnostic examination. By considering the PSNR is well Performed for different noises and different thresholding techniques. From the result it observed Gaussian noise is well performed for Neigh Shrink, Speckle noise is well performed for Min-Max Shrink, Salt and Pepper noise is well performed for Block Shrink.

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