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A Study on Medical Image Denoising using Wavelet and Contourlet Transform

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***Abstract:** In an image processing, the primary intention is to remove the noise from an image. The emergence of noise is due to various internal or external stimuli that creates noise in image. In medical imaging, noisy image leads to false disease identification. Denoising algorithms are introduced to extinguish the noise evocation. By applying Discrete Wavelet Transform (DWT) and Contourlet transform to an input image for image decomposition and preserving edges as well as contours. By employing filter banks at various levels DWT decomposes the signal by down sampling. A Pyramid Directional Filter Bank (PDFB) approximates the input signal and captures the discontinuities to contour linear structures. Wiener Filter (WF), Adaptive Weighted Median Filter (AWMF) and Switching Median Filter (SMF) are used to assist DWT and Contourlet in the process of noise removal. The results of DWT and Contourlet are analyzed based on their performance and other metrics like Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Quality Index (UQI).*

***Keywords:** DWT, Contourlet, WF, AWMF, SMF, PDFB.*

I. INTRODUCTION

Image Denoising plays a key role in Image Processing area. Denoising is one of the famed steps in Image Processing and it is also called as Pre-Processing Phase. It becomes notable for denoise the image before utilizing to the various application. The main aim of denoising is to remove the unwanted noises or signals without losing any information. Image Denoising is an important step in Medical Field. Medical Images are used to divulge the internal structures such as skin and bones. In Medical Field MRI is one of the common tool for diagnosis. Medical diagnosis detects the diseases within the frequent of time.MRI is a miscellaneous safe procedure and it has no pain without exposing the body to ionizing radiation.MRI Images uses magnetic fields to reveal a bones, organs and cartilage. Medical Images are interrupted by variety of noises arising in acquisition process. Noises are corrupted by types of noises such as Additive, Multiplicative and Substitutive Noise. Additive noise is Gaussian noise, Substitutive noises are Salt &Pepper Noise like Impulse noise, .Multiplicative noise is Speckle noise. Medical Images is utmost interrupted by Multiplicative noise. Salt & Pepper noise is randomly repeated, with black and white pixels in an image. To accomplish a noise reduction goal some transforms are used. Contourlet Transform is a Multi-Resolution representation model. Contourlet is basically erect by Filtering bank and Laplacian Pyramid and is used for decomposition and it can recovers the edges and contovers. Wavelet Transform is a Powerful tool for non-stationary signals. In Image Denoising, DWT has attracted for all the researchers. So DWT is often method.DWT performs the levels up to n-level decomposition and different frequency sub bands are generated such as LL, LH, HL and HH.

A. Related Works

Image Denoising is a central pre-processing step in image processing to eliminate the noise in order to strengthen and recover small details that may be hidden in the data [1]. Its main aim is to recover the best estimate of the original image from its noisy versions [14].

Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector [5].A noise can be categorized depending on its source, frequency spectrum and time characteristics. Depending on a source, the noises are categorized into : acoustic noise; thermal and shot noise; electromagnetic noise; electrostatic noise; channel distortions, echo and fading; processing noise [26].

Wavelet transform is a mathematical technique that decomposes the signal into series of small basis function called wavelets. It allow the multiresolution analysis of image and is well localized in both time and frequency domain. As a result of wavelet transform the image is decomposed into low frequency and high frequency components. The information content of these sub images that corresponds to Horizontal, Vertical and Diagonal directions implies unique feature of an image[2].

Contourlet transforms is by introducing basis functions which are local directional, and with multiresolution expansion. This representation has two basic building blocks, the Laplacian pyramid (LP) and the Directional Filter Bank (DFB).A computationally efficient iterative double filter bank structure proposed in [18, 20] uses Laplacian pyramid [32] to capture the point discontinuities, followed by a directional filter bank [29] to connect point discontinuities into linear structures [20].

Filtering is a vital part of any signal processing system, which entails estimation of signal degradation and restoring the signal satisfactorily with its features preserved intact. The filters having good edge and image detail preservation properties are highly desirable for visual perception [30] [26].

Objective quality measures are based on a mathematical comparison of the original and processed or enhanced image and can give an immediate estimate of the Perceptual quality of an image enhancement algorithm[11][13].

B. Motivation and Justification:

Image Denoising is a well-known good model for noise removal and edge preservation. DWT Transformation is a foremost aim for all researchers.DWT is a Muti scale approximation (or) Multiresolution analysis. DWT can bestow a limited directionality and it is also has an essential feature for multi-dimensional signals. DWT transform is efficient method for decomposition and it decomposes the lower coefficients to procure next level approximations and detailed coefficient. In DWT computational cost is high but after denoising Image fidelity is visually lossless.DWT gives a non-redundant and sole representation of the signals.DWT has many Properties such as Multiresolution, Sparsity, Edge clustering and Edge detection. It can capture both location and frequencies information and it also furnish the excellent locality in both frequency and time domain. Contourlet is one of the transformation function. Contourlet is builded by Laplacian Pyramid and Filtering bank. Laplacian Pyramid is used to perceive the line discontinuities and filtering bank is used to tie-up the discontinuities. Edges are clearly discern in contourlet transform. It will speed up the enactment process. It recovers the edges and the shapes. Contourlet gives high degree of directionality. It can easily symbolize the curves and lines without discontinuity.

C. Organization Of The Paper

The rest of the paper is organized as follows. Methodology includes the outline of the proposed work of Contourlet and DWT Transforms, Filtering techniques are presented in Section II. Experimental results are shown in Section III. Performance evaluations are discussed in Section IV and Finally Conclusion is shown in Section V.

II. METHODOLOGY

A. Outline Of The Proposed Work

The input image is added with speckle and salt & pepper noise and applies DWT and Contourlet to decompose the image. Then apply filters in both transforms and noises are removed to obtain the noise free images

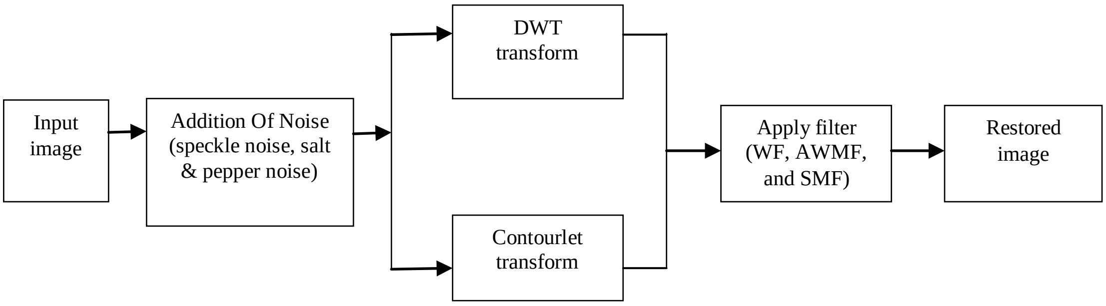


Fig 1. Image denoising block diagram for DWT & Contourlet transform

B. DWT

Wavelet denoising attempts/tries to remove noise which is present in the signal while retaining all the signal characteristics regardless of its frequency contents. The frequency sub-band LH is used to constitute the vertical details of the image, HL contains the horizontal details of the image and the HH sub-band contains the diagonal details of the image. The LL sub-band that is the approximation of the digital image could be further decomposed with the use of discrete wavelet transform to get any level of decomposition of the digital content and it will generate the further four sub-bands. Sub band LL caries approximate element of image, LH contain the vertical element of image, HL contain the horizontal element of image and HH contains diagonal element of image. Thus the information of image is stored in decomposed form in these sub bands[33].

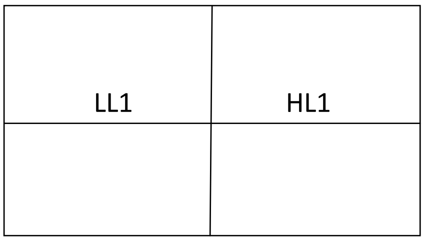


Fig.2 Decomposition of image at Level 1

C. Wavelet families:

1. Haar wavelet:

The Haar wavelet transform may be considered to pair up input values, store the difference and passing the sum. This process is repeated again and again, pairing up the sums to provide the next scale, finally results in differences and one final sum. The Haar wavelet is a simple form of compression which involves average and difference terms, storing detail coefficients, eliminating data, and reconstruct the matrix so that the resulting matrix is similar to the initial matrix[19].*2. Symlets:*

The family of Symlet wavelet is short of "symmetrical wavelets". Symlets are "symmetrical wavelets". They are designed so that they have the least asymmetry and maximum number of vanishing moments for a given compact support[4].

3. Daubechies Wavelets:

Ingrid Daubechies invented what are called compactly supported orthonormal wavelets , one of the brightest stars in the world of wavelet research, thus making discrete wavelet analysis practicable [7].

D. The Contourlet Transform

The Contourlet Transform (CT) is a directional multiresolution image representation scheme proposed by Do and Vetterli, which is effective in representing smooth contours in different directions of an image, thus providing directionality and anisotropy [21]. The framework of the contourlet transform in (fig.3) [29] links point discontinuities into linear structures. The LP provides the means to obtain multiscale decomposition. In each decomposition level it creates a down sampled low pass version of the original image and a more detailed image with the supplementary high frequencies containing the point discontinuities. This scheme can be iterated continuously in the low pass image and is restricted only by the size of the original image due to the down sampling. The simplified DFB used for the contourlet transform consists of two stages, leading to *2l* subbands with wedge-shaped frequency partitioning [28]. The first stage is a two-channel quincunx filter bank [31] with fan filters that divides the 2D spectrum into vertical and horizontal directions. The second stage is a shearing operator that just reorders the samples. By adding a shearing operator and its inverse before and after a two-channel filter bank, a different directional frequency partition is obtained (diagonal directions).

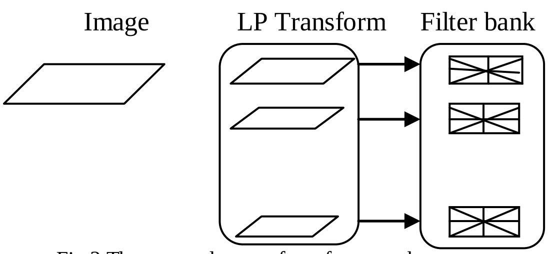


Fig.3 The contourlet transform framework.

By combining the LP and the DFB, a double filter bank named Pyramidal Directional Filter Bank (PDFB) is obtained. Band pass images from the LP decomposition are fed into a DFB in order to capture the directional information. The combined result is the contourlet filter bank. [16].

D. Noise Models

1. Speckle 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 [27]. Thus, denoising or reducing the noise from a noisy image has become the predominant step in medical image processing. For the quality and edge preservation of images [22].

$$g(x,y)=f(x,y)*n(x,y) \qquad (1)$$

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

2. Salt and Pepper Noise

Pepper and Salt noise are a form of the noise classically seen on the images. Salt and pepper noise represents itself as randomly happening black and white pixels. Pepper and Salt noise creeps into images in circumstances where quick transients, such as defective switching, take place. Salt and pepper noise is random in nature, it distributed randomly in the image pixel values [25].

D. Filtering Techniques

1. Wiener Filter

Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. It is not an adaptive filter. The wiener filter's main purpose is to reduce the amount of noise present in an image by comparison with an estimation of the desired noiseless image. The Wiener filter may also be used for smoothing [8]. The goal of the Wiener filter is to filter out noise that has corrupted a signal.

$$F(U,V) = \left[\frac{H(U,V)^{*}}{H(U,V)^{2} + \left[\frac{S_n(u.v)}{S_f(u,v)} \right]} \right] G(U,V) \quad (2)$$

where H(u,v) is the degradation function $H(u,v)^*$ is its conjugate complex and G(u,v) is the degraded image. Functions $s_f(u,v)$ and $s_n(u,v)$are power spectra of the original image and the noise[3].

2. Adaptive Weighted Median Filter (AWMF)

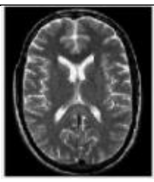
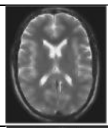
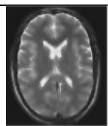
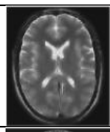
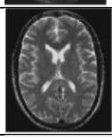
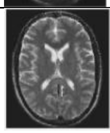
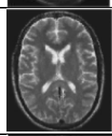
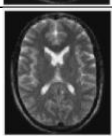
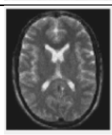
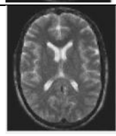
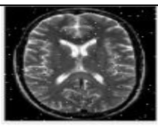
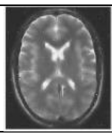
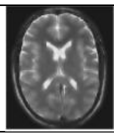
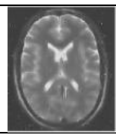
The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by noise. The Adaptive Median Filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as a noise [24]. Adaptive median filter works on a rectangular region Sxy. It changes the size of S xy during the filtering operation depending on certain conditions [9].

3. Switching Median Filter (SMF)

The SMF will provide better denoising in an image [15][17][14]. The switched median filter it switches for the certain condition. We take the window size to be 3×3 in the matrix. Then we calculate the maximum value in the window Wmax, the mini mum value Wmin and the median value M.When Wmin<M && M< Wmax, if this condition satisfies then we replace the fifth value in the window if not the condition is checked if it is satisfied then the median value is replaced or else the mean value of the window is replaced.

III. EXPERIMENTAL RESULTS

Experiments were conducted to denoise a MRI Slicing image is shown in Fig 3 as original image.Speckle and Salt & Pepper noises are added with original image. For various wavelet bases are decomposed with the level 1 and filters are applied. In fig 4 and 6 wavelet bases and contourlet denoised image is shown. Apply the noise variance for the best filter in DWT and Contourlet. Results are shown in fig 5 and fig 7.

Noise	Noisy Image	Filters	Wavelet Type		
			HARR	SYM	DB4
Speckle		WF			
		AWMF			
		SMF			
Salt & Pepper		WF			

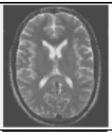
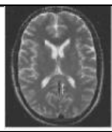
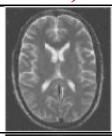
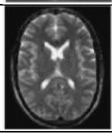
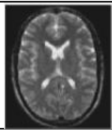
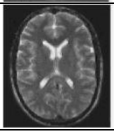
		AWMF			
		SMF			

Fig 4 Wavelet bases for denoised image

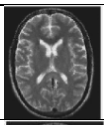
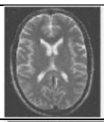
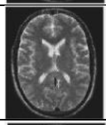
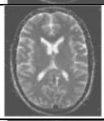
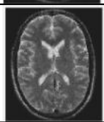
Noise Variance	Speckle Noise For DB4 with AWMF Filter	Salt & Pepper Noise For DB4 with AWMF Filter
0.01		
0.02		
0.04		
0.06		
0.08		

Fig 5 Wavelet bases for denoised image

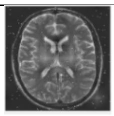
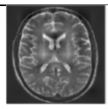
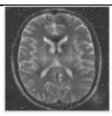
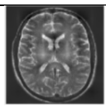
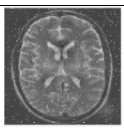
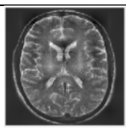
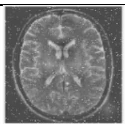
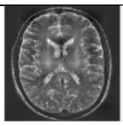
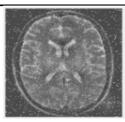
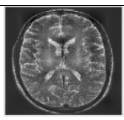
Noise Variance	Speckle Noise For SMF Filter	Salt & Pepper Noise For AWMF Filter
0.01		
0.02		
0.04		
0.06		
0.08		

Fig 6 Contourlet for denoised image

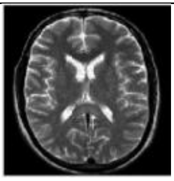
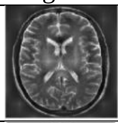
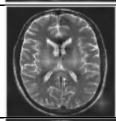
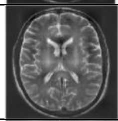
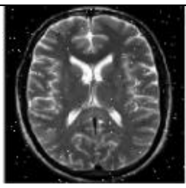
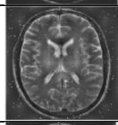
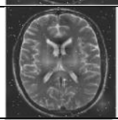
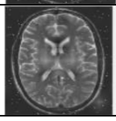
Noise	Noisy Image	Filters	Denoised Image
Speckle		WF	
		AWMF	
		SMF	
Salt & Pepper		WF	
		AWMF	
		SMF	

Fig 7 Contourlet Noise variance with filter

A. Performance Parameters

1. Peak Signal to Noise Ratio (PSNR)

It is the ratio between maximum possible power of a signal and the power of corrupting noise that affects the quality and reliability of its representation. PSNR is calculated as

$$PSNR = 10 Log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (3)$$

Where MSE is mean square error and MAX is the maximum pixel value of image [6].

2. Structural Similarity Index (SSIM):

It is a method for measuring the similarity between two images. The SSIM measure the image quality based on an initial distortion-free image as reference.

$$SSIM = \frac{(2\mu_X \mu_y + c_1)(2\sigma_{x,y} c_2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)} \qquad (4)$$

μ_x the average of x;

μ_y the average of y;

σx^2 the variance of x;

σy^2 the variance of y;

$C_1 = (k1L)^2$ and $C2 = (k2L)^2$ are two variables to stabilize the division with weak denominator. L the dynamic range of the pixel-values k1 = 0.01 and k2 = 0.03 by default. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data [12].

3. Universal quality index

Universal quality index [14] is the new parameter for comparison of quality of the image. Let x= {xi|i=1,2,…,N} and y={yi|i=1,2,…,N} be the original and the test image signal respectively. The quality index Q is defined as:

$$Q = \frac{4\sigma_{XY}\overline{x}\overline{y}}{\left(\sigma_x^2 + \sigma_y^2\right)\left[\left(\overline{x}\right)^2 + \left(\overline{y}\right)^2\right]} \qquad (5)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})$$

The range of Q is [-1, 1]. The ideal value Q=1 will achieve iff yi=xi for all i=1, 2, N, i.e. both images are same [23].

B.Performance Evaluation:

In performance evaluation, the different wavelet bases, contourlet transform and filtering techniques were presented. Performance is calculated by PSNR, SSSIM, and UQI. In TABLE I the different wavelet bases are presented, considering all the performances Harr and DB4 perform well. By varying the noise levels, results are taken and shown in TABLE II and TABLE III.

TABLE I Wavelet bases vs Filter

Noise	Filter	PSNR			SSIM			UQI		
		HARR	SYM	DB4	HARR	SYM	DB4	HARR	SYM	DB4
Speckle	WF	24.003	24.1356	24.2718	0.7173	0.7198	0.7227	0.5692	0.5493	0.5306
	AWMF	24.133	24.9792	**25.1084**	0.71736	0.85219	0.8533	0.56922	0.76583	0.7382
	SMF	21.8522	21.9859	22.0573	0.76134	0.76102	0.7578	0.7611	0.71625	0.6690
Salt & Pepper	WF	23.0618	22.9344	23.2063	0.62277	0.61724	0.62729	0.49115	0.4785	0.48094
	AWMF	**25.1878**	24.9787	24.7982	0.89031	0.84263	0.82899	0.81929	0.72701	0.69061
	SMF	22.2738	22.2131	22.2749	0.83249	0.78097	0.77993	0.82465	0.68849	0.65654

TABLE II Noise variance vs AWMF Filter

Salt & Pepper Noise For HARR with AWMF Filter			
Noise Variance	PSNR	SSIM	UQI
0.01	25.1878	0.89031	0.81929
0.02	24.2867	0.8529	0.78928
0.04	22.8129	0.78373	0.71942
0.06	21.2415	0.68872	0.63822
0.08	19.8736	0.58789	0.55453

TABLE III DWT for Noise variance vs AWMF filter

Speckle Noise For DB4 with AWMF Filter			
Noise Variance	PSNR	SSIM	UQI
0.01	25.1084	0.85335	0.73825
0.02	24.3656	0.80925	0.69909
0.04	23.1886	0.74683	0.64674
0.06	22.3305	0.70491	0.61399
0.08	21.6587	0.67243	0.58546

TABLE IV Contourlet for denoised image

Noise	Filter	PSNR	SSIM	UQI
Speckle	WF	20.2374	059294	0.59410
	AWMF	20.9769	0.80151	0.66882
	SMF	**21.6933**	0.73157	0.6193
Salt & Pepper	WF	19.0673	0.57679	0.55778
	AWMF	**20.9147**	0.73412	0.64036
	SMF	20.1727	0.67604	0.58771

TABLE V Contourlet for Noise variance vs SMF Filter

Speckle Noise For SMF Filter			
Noise Variance	PSNR	SSIM	UQI
0.01	21.6933	0.73157	0.6193
0.02	21.0955	0.67535	0.57781
0.04	20.1196	0.60199	0.52122
0.06	19.3355	0.55924	0.49138
0.08	18.6814	0.52392	0.46078

TABLE VI Contourlet for Noise variance vs AWMF Filter

Salt & Pepper Noise For AWMF Filter			
Noise Variance	PSNR	SSIM	UQI
0.01	20.9147	0.73412	0.64036
0.02	19.4268	0.64335	0.56337
0.04	17.339	0.49443	0.45567
0.06	15.8522	0.3977	0.3839
0.08	14.7028	0.32847	0.3300

In TABLE I speckle noise provides better result for DB4 and salt & pepper noise provides better result for Harr. In DWT, AWMF Filter is the best for both speckle and salt & pepper noise and apply the noise variance for best filter results are taken and shown in TABLE II and TABLE III. In contourlet it identifies the SMF Filter and AWMF filter shown in TABLE IV then apply the noise variance for best filter that is shown in TABLE V and TABLEVI

IV. CONCLUSION

This paper presents a comparative analysis of image denoising techniques using wavelet transforms and Contourlet transforms. DWT and Contourlet is a good tool for image denoising. Filtering techniques are used to enhance the edges and increases the image clarity. We have experimented with three different filters (WF Filter, AWMF Filter and SMF Filter*)*. It is contaminated with Gaussian noise, salt and paper noise and speckle noise. The Qualitative measure such as PSNR, SSIM, and UQI are used. In DWT, DB4 performed well against speckle noise for AWMF filter and Harr performs well against salt & pepper for AWMF filter. In Contourlet, AWMF filter is well suited for salt & pepper and SMF Filter is well suited for speckle noise.

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