ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

Quantum Noise Removal in Breast Mammogram Images using Thresholding Shrinkage Techniques

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ABSTRACT: Noise Reduction in Medical Images plays a principal role in the field of image processing. It is the basic procedure for image enhancement, segmentation, feature extraction and image analysis. The Main aim of image denoising is to remove the noise with visually high quality images as well as to preserving edges is also very important. Medical images are repeatedly corrupted by noise during its acquisition and transmission. Noise is unwanted electrical or electromagnetic energy that degrades the quality of signals and data. In this paper, we have taken Mammographic Images. Mammogram images are exploited by Quantum Noise during its acquisition because of low-count X-ray photons. To remove the Quantum Noise in mammogram image, Discrete Wavelet Transform(DWT) are used. Discrete Wavelet Transform are very effective because of its characteristics of sparcity, multiresolution and straightforward technique. In this work, various threshold shrinkage techniques has been used to remove quantum noise. Various Thresholding techniques such as VisuShrink, BayesShrink, SureShrink, NeighShrink. The performance metrics such as Peak Signal to Noise Ratio(PSNR), Mean Structural Similarity Index Measure(MSSIM), Mean Absolute Error(MAE),Normalized Cross Correlation(NCC) , Normalized Absolute Error(NAE) are used to evaluate the denoising performance.
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KEYWORDS: Mammogram images; Quantum Noise; Discrete Wavelet Transform(DWT); Threshold Shrinkage Techniques

I. INTRODUCTION

Image Denoising is the major part of image enhancement in the field of image processing. The images are corrupted by various types of noises such as Gaussian Noise, Speckle Noise, Rician Noise, Salt and Pepper Noise during its acquisition or transmission. When the Noise is introduced in medical images ,decreases its image quality as well as it will affect its further processing. The next level processings are image enhancement, segmentation, image analysis will become difficult to diagnose it accurately. Therefore, Noise Reduction in medical images plays an important role in image denoising. In this paper, We have taken Mammogram images. Mammogram is an X-ray image of women's breast used to screen for breast cancer. Mammogram plays a key role in early breast cancer detection and help decrease breast cancer deaths. Mammogram images are used to detect breast cancer in women at the age of 35 to 55. It is a specific type of breast imaging that uses low-dose x-rays to detect cancer early before women experience symptoms. Breast Cancer is a malignant tumor(a collection of cancer cells) arising from the cells of the breast.

There are various methods for noise removal techniques in image denoising. To remove noises in mammogram images, Discrete Wavelet Transform is one of the methods in image denoising. In Discrete Wavelet Transform, the wavelets are discretely sampled. It captures both Frequency and location information. Discrete Wavelet Transform performs in frequency and time domain. Wavelet Transform provide signals in time and frequency domain simultaneously. An image is decomposed using wavelet transform, it has two function. One is wavelet function and another one is scaling function. Wavelet function is used to represent the low frequency component that is detail part of an image and scaling function is used to represent low frequency component that is smooth part of an image. Wavelet Transforms construct the signal energy concentrate in a small number of coefficients. To remove the noises, threshold shrinkage techniques are used such as VisuShrink, SureShrink, NeighShrink, BayesShrink.

A. Motivations and Justification

Breast cancer is one of the leading cause of deaths for women and it is fount at the age between 35 and 55. Early breast cancer detection is very important for breast cancer. Mammography is the best screening tool for detecting the breast cancer early. Quantum noise occurs in mammogram images during acquisition due to low count x-ray photons. Motivated by these facts, inspiring to denoising the mammogram image for detecting the breast cancer.

Discrete Wavelet Transform is used to denoising the mammogram image. Because Wavelet Transform is used to analyse the stationary signals and non-stationary signals. Wavelet Transform offers simultaneous localization in time and frequency domain. Wavelet Transform is used to separate the fine details in a signal. Small wavelets used to isolate very fine detail in a signal and very large wavelets used to identify coarse details in a signal. Motivated by these facts, we are inspired to denoising a mammogram image in Discrete Wavelet Transform. Therefore I justified that the Discrete Wavelet Transform is well suited in mammogram image Denoising.

B. Organisation of the paper

The remaining paper is organised as follows:- Section II includes Methodology which includes outline of the proposed work, Section III includes Experimental Results, Section IV includes Performance Evaluation and Section V includes Conclusion of the paper.

II. RELATED WORK

Medical image denoising plays major role in image processing. There are variety of medical imaging modalities are present like x-ray, Computed Tomography(CT), Medical Resonance Imaging(MRI), Mammogram. Mammogram is picture of breast capture by using x-rays. Mammography is used as an effective imaging modality for breast cancer screening. Breast cancer is considered to be one of the leading causes of deaths among females on a global level. But the image is corrupted by Quantum noise. Quantum noise occurs in the mammogram images during acquisition due to low-count x-ray photons. It affects the quality of the images[8].

A mammogram image is affected by three types of noises such as Gaussian Noise, Poisson Noise(Quantum Noise),white noise. In this paper, mammogram image is exploited by quantum noise[14]Quantum noise is non-additive and signal-dependent(that is, noise components values are correlated with respect to the radian intensity)[9] Detection and diagnosis of breast cancer in its early stage increase the successful treatment and complete recovery from disease. An effective technique is necessary to propose to detect cancer in the early stages is very important. Mammography has been proved to be the most reliable method and it is the key screening tool fr the early detection of breast cancer[15] Noise Reduction in mammogram images, DWT is the one of the methods used in image processing. Using Discrete Wavelet Transform(DWT) method of denoising, the image is decomposed in the form of discrete wavelets and after reconstruction it forms inverse discrete wavelet transform which holds the denoised image[16]. DWT use a specific subset of scale and translation values. Based on these basis function wavelets are classified as Haar, Coiflet, Daubechies, Symlet, Biorthogonal etc[13].

There are several wavelet families Daubechies, Haar, symlet, Shannon, coiflet have been performed for noise removing. There are two categories of wavelet bases: Orthogonal and BiOrthogonal. Orthogonal wavelets are daubechies, Coiflet, Symlet.

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 [3,4]. 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[12]. The reverse biorthogonal family uses the synthesis functions for the analysis and vice versa.

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ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 4, Issue 5, May 2016

III. METHODOLOGY

A. Outline of the Proposed Method

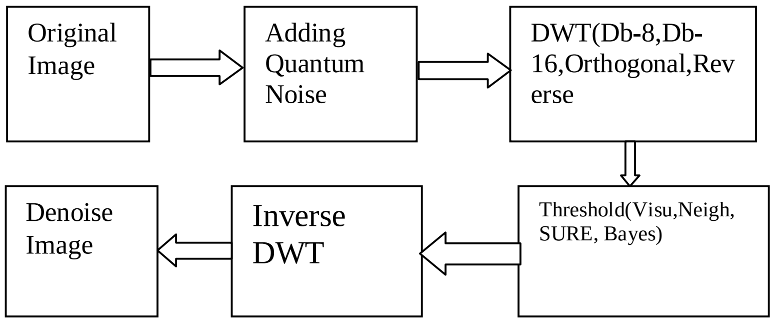

Fig1. Block Diagram of denoising mammogram image using threshold shrinkage techniques

- Get the input image and adding poisson noise
- Apply Discrete Wavelet Transform(Db-8, Db-16, Biorthogonal, Reverse Biorthogonal) Transform on noisy image to get the noisy coefficients
- Apply Threshold Shrinkage Techniques on the noisy coefficients to get the denoised image.
- In our proposed work , to find the best wavelet base and best shrinkage techniques.

B. Poisson Noise

Poisson Noise is induced by the nonlinear response of the image detectors and recorders. This type of noise is image data dependent. Poisson noise is also called Quantum Noise. This term arises because detection and recording processes involve random electron emission having a Poisson distribution with a mean response value. Since the mean and variance of a poisson distribution are equal, image dependent term has a standard deviation if it is assumed that the noise has a unity variance[17]

Probability Density Function for poisson noise given below.

$$f(X/\lambda)=\frac{\lambda^{x}}{x!}e^{-\lambda};x=0,1,2,3..... \tag{1}$$

e is Euler's Number(e=2.71828) x! is the factorial of x, The positive real number λ is equal to the expected value of X and also to its variance

C. 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

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.

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Vol. 4, Issue 5, May 2016

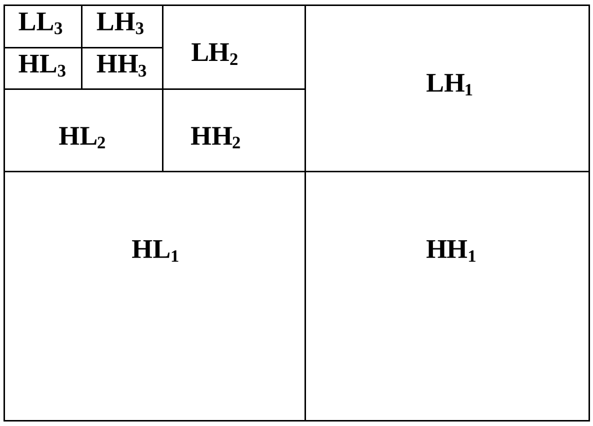

Fig.2 Three Level Decomposition in Discrete Wavelet Transform

1,2,3 – Decomposition Level
H----High Frequency Bands
L-----Low Frequency Bands

D. Wavelet Shrinkage Thresholding Techniques

To denoise an image,the following threshold shrinkage techniques to be used.
The techniques are:- VisuShrink,SUREShrink,NeighShrink,BayesShrink.

A. Visu Shrink

It follows the hard threshold rule. The drawback of this shrinkage is that neither speckle noise can be removed nor MSE can be minimized deal with additive noise Threshold T can be calculated using this formula[10]

$$T_v = \hat{\sigma}\sqrt{2logN}$$

$$\hat{\sigma}^2 = \left[\frac{median(|X_{ij}|)}{0.675}\right]^2, X_{ij} \in HH1 \quad (2)$$

Where σ is calculated as mean of absolute difference (MAD) which is a robust estimator and N represents the size of original image.

B. 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

$$\hat{\sigma}_y^2 = \hat{\sigma}_x^2 + \hat{\sigma}_n^2 \quad (3)$$

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

$$t_B = \frac{\partial n^2}{\partial_x} \quad (4)$$

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

$$\hat{\sigma}_X = \sqrt{\max\left(\hat{\sigma}_y^2 - \hat{\sigma}_n^2, 0\right)} \quad (5)$$

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

C. NeighShrink

Let **g**= $\{g_{ij}\}$ will denote the matrix representation of the noisy signal. Then, *w* W_g denotes the matrix of wavelet coefficients of the signal under consideration. For every value of w_{ij}, let B_{ij} is a neighbouring window around

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w_{ij} , w_{ij} denotes the wavelet coefficient to be shrinked. The neighbouring window size can be represented as L, where Let

$$S_{ij} = \sum_{(k,l)\in B_{ij}} w_{kl}^2 \quad (6)$$

We omit the corresponding terms in the summation when the above summation has pixel indexes out of the wavelet sub-band range. The shrinked wavelet coefficient according to the
neighshrink is given by this formula[6]

$$\acute{w}_{ij} = w_{ij}\beta_{ij} \quad (7)$$

The shrinkage factor β_{ij} can be defined as:

$$\beta_{ij} = \left(1 - T_{UNI}^2 / S_{ij}^2\right)_+ \quad (8)$$

here, the + sign at the end of the formula means to keep the positive value while set it to zero when it is negative and T_{UNI} is the universal threshold, which is defined as[1]

$$T_{UNI} = \sqrt{2\sigma^2 \ln(n)} \quad (9)$$

where n is the length of the signal.
Different wavelet coefficient sub-bands are shrinked independently, but the universal threshold T_{UNI} and neighbouring window size L kept unchanged in all sub-bands.

D. SureShrink

SureShrink works on the principle of Stein's Unbiased Risk Estimator(SURE) proposed by[2]. Threshold value t_j for each resolution level j in the wavelet transform is used, which is referred to level dependent thresholding. The SureShrink threshold t^* is defined as follows:--

$$t^* = min\left(t, \hat{\sigma}_n\sqrt{2 \times \log(n)}\right) \quad (10)$$

Where t denotes the value that minimizes Stein's Unbiased Risk Estimator. Sure Shrink minimizes the mean squared error and also it is smoothness adaptive,which means that if any unknown function includes abrupt changes or boundaries in the image, the reconstructed image also has the same. [11]

IV. EXPERIMENTAL RESULTS

Experiments were performed to denoising a mammogram breast image is shown in Fig. 3. To denoise the mammogram images with different wavelet bases such as Daubechies, Biorthogonal, Reverse Biorthogonal using poisson noise is shown in Fig. 4.

Fig.3 Original Mammogram Breast Image

ISSN(Online): 2320-9801
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International Journal of Innovative Research in Computer and Communication Engineering

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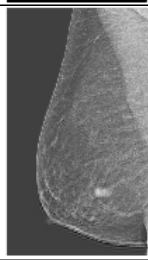
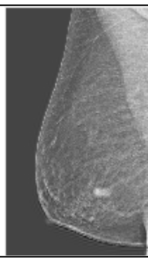
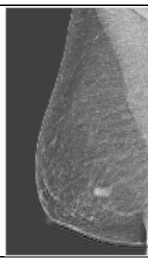
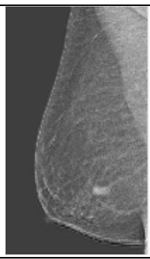
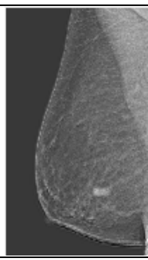
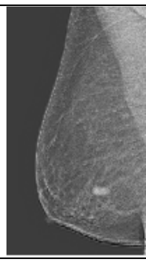
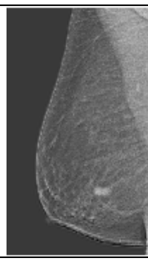
Wavelet Transform		**Visushrink**	**Neighshrink**	**Sureshrink**	**Bayesshrink**
Noisy Image					
Denoised Images Using Differet wavelet Bases	DB-8				
		Denoised image using Daubechies-8 Wavelet at Level 1 with VisuShrink	Denoised image using Daubechies-8 Wavelet at Level 1 with NeighShrink	Denoised Images using Daubechies-8 Wavelet at Level 1 with SureShrink	Denoised Images using Daubechies-8 Wavelet at Level1 with B BayesShrink
	DB-16				
		Denoised image using Daubechies-16 Wavelet at Level 1 with VisuShrink	Denoised image using Daubechies-16 Wavelet at Level 1 with NeighShrink	Denoised image using Daubechies-16 Wavelet at Level 1 with SureShrink	Denoised image using Daubechies-16 Wavelet at Level 1 with BayesShrink
	Biorthogonal				
		Denoised image using Biorthogonal Wavelet at Level 1 with VisuShrink	Denoised image using Biorthogonal Wavelet at Level 1 with NeighShrink	Denoised image using Biorthogonal Wavelet at Level 1 with SureShrink	Denoised image using Biorthogonal Wavelet at Level 1 with BayesShrink

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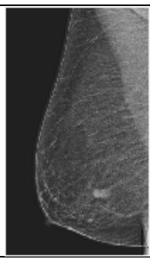
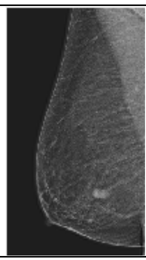
	Reverse Bi-Orhogonal				
		Denoised image using Reverse Biorthogonal Wavelet at Level 1 with VisuShrink	Denoised image using Reverse Biorthogonal Wavelet at Level 1 with NeighShrink	Denoised image using Reverse Biorthogonal Wavelet at Level 1 with SureShrink	Denoised image using Reverse Biorthogonal Wavelet at Level 1 with BayesShrink

Fig.4. Denoising using different wavelet bases with various Threshold Shrinkage Techniques in mammogram image corrupted by poisson noise

IV. PERFORMANCE EVALUATION

A. *Performance Metrics*

The performance metrics is used to evaluate the performance of the denoised image. The metrics are:-PSNR, MSSIM, NCC, MAE.

A. *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[19]

$$PSNR = 20 \log 10(255/RMSE) \tag{11}$$

Higher the PSNR gives lower the noise in the image i.e.,higher the image quality[7,20].

B. *Mean Structural Similarity Index Measure(MSSIM)*

The Structural Similarity Index between two images is computed as[7,20] :

$$SSIBM(x,y) = (2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)/(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2) \tag{12}$$

Where $\mu_x = \sum_{i=1}^{N} w_i x_i$

$\sigma_x = (\sum_{i=1}^{N} w_i (x_i - \mu_x)^2)^{1/2}$, $\sigma_{xy} = \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y)$,

$C_1 = (K_1 L)^2, and C_2 = (K_2 L)^2$

Where L is the range of pixel values(255 for 8-bit grayscale images). And K1<<1 is a small constant and also K2<<1 [20]

$$\boldsymbol{MSSIM = \sqrt{SSIM}} \tag{13}$$

C. *Normalized Cross Correlation (NK/NCC)*

It is a measure of similarity of two images as a function of a time-lag applied to any one of them. It is co relational based quality measure which normally looks at correlation features between the pixels of original and reconstructed image[18]. Normally NK is in the range of 0 to1, very near to or one is the best. This is also known as a sliding dot product or sliding inner-product. It is expressed as

$$NK = \sum_{j=1}^{M} \sum_{k=1}^{N} x_{j,k} . x'_{j,k} \; / \; \sum_{j=1}^{M} \sum_{k=1}^{N} x_{j,k}^2 \tag{14}$$

Where x is the original image and x' is the denoised image, Where M, N are number of rows and columns of an image.

D. *Mean Absolute Error(MAE)*

It is a quantity used to measure closeness of predictions to the true value[17]

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International Journal of Innovative Research in Computer and Communication Engineering

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$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (15)$$

It is an average of absolute errors $'e^i'$. $'f^i'$ is the prediction and $'y^i'$ is the true value.

B. Performance Evaluation

The performance of the Wavelet Families and Thresholding Techniques were examined using the metrics PSNR, MSSIM, RMSE, MAE, NCC/NK. The first experiment is performed to estimate the performance of different wavelet families such as Daubechies,Biorthogonal, Reverse Biorthogonal. Results are shown in Table 1. Taking into considertation of all the metrics, it is surveyed that the Reverse Biorthogonal base performances is better than the the other bases.

Table 1: Different wavelet bases with poisson noise in mammogram images

Threshold Shrinkage Techniques	Different Wavelet Bases	Poisson Noise			
		PSNR	MSSIM	MAE	NCC/NK
VisuShrink	DB-8	24.9386	0.89398	60.662	0.98007
	DB-16	24.746	0.88335	60.6859	0.97905
	Biorthogonal	21.3126	0.71156	61.1666	0.96806
	Reverse Biorthogonal	25.9517	0.90945	62.2845	1.0085
NeighShrink	DB-8	24.9128	0.89636	60.6644	0.97991
	DB-16	24.7506	0.88353	60.7145	0.97896
	Biorthogonal	21.3305	0.712	61.2029	0.96816
	Reverse Biorthogonal	25.9324	0.90963	62.2259	1.0084
SureShrink	DB-8	24.973	0.89446	60.6276	0.98003
	DB-16	24.7306	0.88238	60.6932	0.97892
	Biorthogonal	21.3031	0.71202	61.178	0.9679
	Reverse Biorthogonal	25.9	0.90896	62.2345	1.0082
BayesShrink	DB-8	24.899	0.89293	60.6557	0.97993
	DB-16	24.7598	0.88345	14.7419	60.6914
	Biorthogonal	21.282	0.71162	61.1999	0.96783
	Reverse Biorthogonal	25.9211	0.90892	62.2727	1.0085

From Table 1, it is noted that the wavelet families are best fit for poisson noise.All type of wavelet family are equally perform well in removing poisson noise. It is observed that the performance of Reverse Biorthogonal wavelet base is somewhat better than other bases.

V. CONCLUSION

This paper presents Mammogram breast Image Denoising Using Different Wavelet bases with Thresholding Shrinkage Techniques. Experiments were performed to analyse the best wavelet bases such as Daubechies(Db-8,Db-16), BiOrthogonal, Reverse BiOrthogonal. When using wavelet transform, the choices of choosing a wavelet bases have a great impact on the success of thresholding shrinkages techniques. Thresholding Shrinkage techniques like VisuShrink, NeighShrink, SureShrink, BayesShrink have been applied.

Performance Metrics such as PSNR, MSSIM, MAE, NCC are used to evaluate the denoising effect. It is observed from all wavelet bases, Reverse Biorthogonal performs well in federation with VisuShrink for removing poisson noise.

ISSN(Online): 2320-9801
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International Journal of Innovative Research in Computer and Communication Engineering

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