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Image Denoising Using Adaptive Bivariate-Bayesian Threshold in Multi Wavelet Packet Transform

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Abstract:
The basic aim of Image Denoising is to reduce the noise and modify the important features present in the corrupt signal. Researchers have been doing it in one way or the other since long time. In this paper, we present a new adaptive Bivariate-Bayesian soft threshold denoising scheme using multi wavelet packets. Bayes estimation and Bivariate wavelet soft thresholding overcome the shortcomings of each other. Our algorithm is capable of dealing with highly contaminated images. Simulation results show that Bivariate-Bayesian soft threshold has better perform over existing adaptive threshold denoising techniques viz. Bayesshrinkage, Maximum A Posterior (MAP) shrinkage, Ogawa shrinkage, etc. The quality parameters like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), L2 Norm and Structure Similarity (SSIM) Map were used for the comparison of the performance.

Keywords: *Bivariate-Bayesian threshold, Multi Wavelet packet Transform, Wiener prune filter, PSNR, MSE and L2 Norm.*

1. Introduction

Researchers have been developing new techniques for image denoising since about last two decades. Removal of inherent noise from an image is referred to as image denoising. However, noise is characterized by its corresponding probability distribution function like Gaussian, Poisson, etc. Usually all statistical properties of a noise distribution are required to be explored for effective image denoising, like standard deviation, variance, etc. [i-vi].

Mallat has proposed transform domain filtering [iv]. It basically utilized the concept of basic functions. The most suitable transform domain filtering in denoising is wavelet Transform. Wavelet transform is based on the non-linear thresholding technique. It exploits the sparsity property.

Simoncelliet al. have proposed Bayesian estimator [v] that is an extension of Wiener estimator. It performs a coring operation and exploits the higher order statistics (i.e. smoothness and edges) using sub-bands strategy. We have been observed the Bayesian estimator itself is not the preferred choice of sub-band transform because of it produces blurred images. In order to achieve less blurring and image compression or texture synthesis, we require better statistical model. Therefore, Chipman et al. [vi] proposed adaptive Bayesian estimator for fixing the prior parameters at each resolution, results level dependent shrinkage function is getting introduced. Their algorithm obtains an intuitively appealing shrinkage function to resolve the structure problem in Wavelets but uncertainty in a reconstruction is quantified and displayed.

Shui et al. [vii] have proposed wiener cost function to produce the best wavelet packet coefficients of the noisy image. This algorithm produces the better compression performance than standard wavelet. But this algorithm is used pilot signal whereas practically prior is required. This algorithm works on single wavelet packet whereas multi wavelet packet is required for in-depth suppression of noisy coefficients, when noise is high. Fathi et al. [viii] have proposed an adaptive wavelet packet thresholding function based on Generalised Gaussian Distribution (GGD). This algorithm is based on multi level 3 wavelet packet thresholding. This algorithm depends upon sub-band and statistical parameters. Computational cost of the algorithm is modest.

The paper is illustrated in the following manner. Section *1.1.* shows problem formulation. The proposed Bivariate-Bayesian threshold using multi wavelet packet is employed in Poisson-Gaussian noise model has been comprehensively discussed in section *1.2.*. Results show proposed Bivariate-Bayesian threshold is outstanding perform after simulation and described in section *1.3.*. Finally, concluding the objective is to satisfy the overall remarks in section 2..

1.1. Problem Formulation

However a selection of an optimal multi wavelet packet threshold for a multi resolution concept is still an open area of research and has been taken up in this work. Keeping this point in view, structural adaptive threshold techniques have been proposed by us.

1.2. Proposed Method

In wavelet denoising people have been doing thresholding, for example, Visu shrink. This universal threshold produces over smooth image owing to it cleaned large wavelet coefficients. There after wavelet adaptive threshold was introduced like Stein Unbiased Risk Estimator (SURE) [i-vi]. SURE suppressed noise in relative sub-bands instead of overall samples but reduces important features such as lines, corners, borders and edges.

Recently effective adaptive wavelet shrinkage methods were developed inside in the sub-band among Bivariate-Bayesian threshold is one. This data driven method has some parameters like shape parameter (β) and standard deviation of detail sub-band (σ_x) are estimated by Bivariate-Bayesian threshold [vii-ix]. Bayesian rule overcomes the shortcoming of wavelet transform. Moreover, Bayesian model together with wavelet packets permit prior information of signal and higher computation speed.

First of all the authors have developed Dual Tree Wavelet Packet Transform (DTWPT) based on [ix-x] in Bayesian paradigm. DTWPT exploits the advance features such as directionality and shift invariance while as Discrete Wavelet Transform (DWT) suffers from lack of directionality and shift invariance. DTWPT offers the wider range of possibilities of frequency resolution. Therefore, DTWPT of a 2D image can be obtained by employing two separable 1D wavelet packets in each direction.

$$W_{j,s}^{p} = W_{j+1,s}^{2p} \oplus W_{j+1,s}^{2p+1}$$

By inspiring the state of art wavelet packets denoising theory our center of interest on two main points.

1) First, no methods were focused on very inner part of the sub-band taking wavelet packets.
2) Second, normally all methods are illustrated on Gaussian or Poisson distribution but have not been developed with a combined effort of Poisson-Gaussian distribution.

After DTWPT, true image are added with noisy image z distorted by Gaussian-Poisson noise.

$$g = f + \sigma_n * z \qquad (1)$$

Taking the cue from equation (1) we generate where σ_n is noise standard deviation needs to be estimated from [xi]

$$\sigma_n = MAD(|H_j H_k|)) \qquad (2)$$

Where, $H_j H_k$ is inner detail sub-band of DTWPT and in this paper we strictly focused on resolution $j = 2$ and translation $k = 2$. DTWPT could be observed as of equation (1) is illustrated in equation (3) with F and Z are independent to each other.

$$G = F + Z \qquad (3)$$

Noisy observation G modeled as zero mean and its noise variance is $\sigma_G{}^2$, variance of original image is $\sigma_f{}^2$ and $\sigma_n{}^2$ is variance of true noise image calculated by MAD.

$$\sigma_G{}^2 = \sigma_{F_x}^2 + \sigma_n^2 \qquad (4)$$

$$\sigma_G{}^2 = \frac{1}{n^2}\sum_{i,j=1}^{n} G_{i,j}^2 \qquad (5)$$

Where $n \times n$ is the maximum size of subband. i and j are rows and columns of transform metrics G.

$$T_B = \frac{\sigma_n^2}{\sigma_{F_x}} \qquad (6)$$

Where, T_B is Bayesian Threshold, σ_n is standard deviation of inner most detail of Wavelet packet.

$$\sigma_{F_x} = \sqrt{\max(\hat{\sigma}_G{}^2 - \hat{\sigma}_n{}^2), 0} \qquad (7)$$

In image denoising, parameter estimation equations such as β and σ_x are subject to quantify the local characteristics of sub-band. These GGD parameters are used to determine the adaptive threshold for each sub-band. Therefore magnitude Bivariate-Bayesian threshold [x] define as

$$T_p = \frac{soft(\sqrt{B^2 + C^2}, T_B)}{\sqrt{B^2 + C^2}} z_+ \qquad (8)$$

Finally, inverse Multi Wavelet packet transform are applied on reconstruction side to obtain the denoised image $\hat{f}(a,b)$ is close to original image $f(a,b)$.

Error is $e(a,b) = \hat{f}(a,b) - f(a,b) \qquad (9)$

That is why Mean square error is

$$MSE = \frac{1}{PQ}\sum_{p=0}^{P-1}\sum_{q=0}^{Q-1}[f(a,b) - \hat{f}(a,b)]^2 \qquad (10)$$

The Peak signal to noise ratio is given by

$$PSNR(f, \hat{f}) = 10\log_{10}\frac{(2^B - 1)^2}{MSE} dB \qquad (11)$$

Whereas B represents number of bits, in MR images it may be 8 or in CT images it may be 9.

1.3. Simulation and Results

The proposed method was performed using MATLAB R2012a on a Dell Laptop with 2GB RAM, Core i-3 processor and windows 7 operating system. The proposed method emphasize that the simulation part in our studies is evaluating the denoised performance of Poisson-Gaussian model. In this framework, we simulated medical images with size 512*512 gray scales. The proposed method can be realized using the sizes of log energy bounded wiener prune filter [vii-xi]are 3x3, 5x5 and 7x7 choosing accordingly with the local noise content. He we were used two case studies for simulation. These are showing below and call as Breast and Rembrandt Diagnosis's.

Sr. no. 1.

Collection ID is Breast Diagnosis, Subject ID is Breast Dx-01-0051, Studies and Series is 2/2 and 6/6, Description is T2W-TSE SENSE, Modality is MR and Manufacturers is Phillips medical systems [xii].

Sr. no. 2.

Collection ID is Rembrandt 1 and 2, Subject ID is 900-00-5308, Studies and Series is - and 17/17, Description not given, Modality is MR and Manufacturers not given [xii].

Multi Wavelet packets analysis is concerned with scales and sub bands present in a signal. The change of values in coefficients from negative to positive and vice versa determines the amount of noise and information in the signal. Our aims are preserved the features during denoising and analyzing the performance of Bivariate Bayes shrink in DTWPT. Bayes estimation and Bivariate wavelet soft thresholding overcome the rational of each other. Both estimators described here using cost estimation behavior of log energy bounded wiener prune filter [vii-xi].

To compare the experimental evaluation of proposed method with various denoising approaches such as Bayes Maximum a Posterior (MAP) shrink [xiii], Ogawa threshold [xiv] and Hari om shrink [xv-xvi].The results are collected using 80 different images on average 20 iterations [xii]. The best one of among methods is highlighted in bold fonts, which are shown in Table 1 through Table 3 and also depicts in Fig. 1 to Fig. 6.

Standard deviation	**Noisy image**	**Bayes MAP Shrink**	**Ogawa Shrink**	**Hari om Shrink**	**Proposed Multi WPT+ Bivariate shrink**
5	34.15	32.08	28.17	26.23	**32.63**
10	28.14	31.67	27.37	26.85	**32.01**
15	24.58	30.91	26.15	26.53	**31.27**
20	22.12	29.24	25.19	23.00	**30.31**
25	20.18	22.61	21.89	19.97	**23.41**
30	18.62	28.05	26.54	26.13	**28.50**
35	17.26	23.45	20.83	19.22	**27.51**
40	16.08	22.09	22.09	22.09	26.78

Table 1: PSNR of denoised MRI Breast Bilateral with T and without Contrast

Standard deviation	**Noisy image**	**Bayes MAP Shrink**	**Ogawa Shrink**	**Neigh Shrink**	**Proposed Multi WPT+ Bivariate shrink**
5	24.95	36.62	40.57	41.57	**35.47**
10	99.72	41.83	46.06	46.01	**40.87**
15	226.03	48.34	49.21	49.33	**48.51**
20	398.84	62.71	64.00	63.90	**60.53**
25	623.75	298.23	311.48	299.23	**296.42**
30	892.55	23.97	23.75	23.97	**91.71**
35	1220.56	120.78	153.39	142.00	**115.33**
40	1600.94	141.66	169.93	156.82	**136.27**

Table 2: MSE of denoised MRI Breast Bilateral with T and without Contrast

Standard deviation	Noisy image	Bayes MAP Shrink	Ogawa Shrink	Neigh Shrink	Proposed Multi WPT+ Bivariate shrink
5	1.009	0.98	0.86	0.85	**0.99**
10	1.037	0.98	0.86	0.85	**0.99**
15	1.088	0.98	0.85	0.83	**0.99**
20	1.155	0.99	0.81	0.80	**1.00**
25	1.241	0.98	0.86	0.85	**1.09**
30	1.339	0.99	0.96	0.95	**1.00**
35	1.475	1.0	0.95	0.93	**1.02**
40	1.612	1.01	0.91	0.90	**1.02**

Table 3: L2R norm of denoised MRI Breast Bilateral with T and without Contrast

We found that for in depth denoising, wavelet method is suitable in conjunction with Bivariate Bayesian threshold but after the execution we have been clearly seen that some part of the noise may left inside in the denoised image. This is the reason for using iterative noise variance and log energy bounded wiener prune filter [vii-xi], in addition. The method is employed on in-depth locations of the sub-bands having higher noise levels to preserve image details. Our proposal is adaptive towards inner most part of wavelet transformation and it is able to used for different purposes like edge detections, feature selections, etc. It is evident by the table that the proposed method outperforms other methods, at most of the time with 5% margin. Also the method is applicable to a large range of noise ratio i.e. 05-40% and keeps its effectiveness in preservation of edges and smoothness. For the comparison of proposed method with other methods like oracle shrink, Bayes shrink, etc., are showing better PSNRs, MSEs and L2 norms. Which are depicting in Table 1 through Table 3.

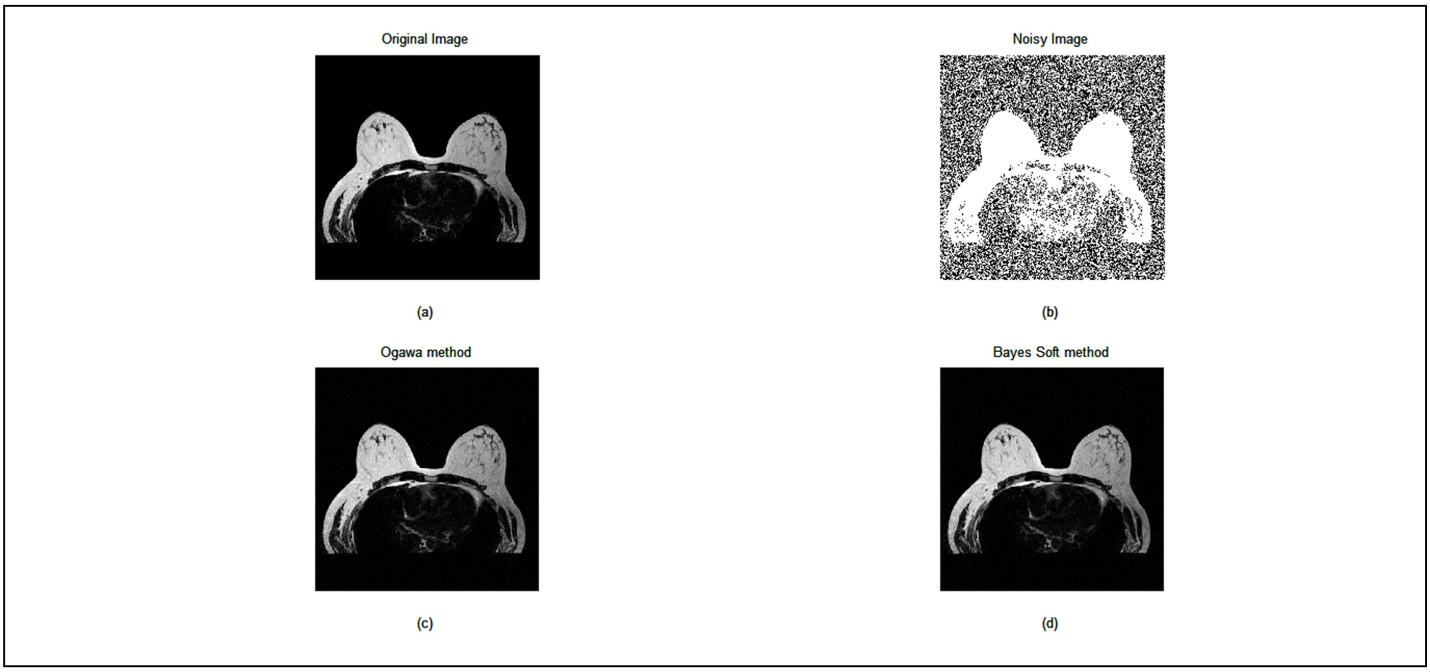

Figure 1 (a) Original image (b) Poisson Gaussian noise under scaled image (c) Ogawa method (d) Bayes Soft, All processes performed at σ_n =40.

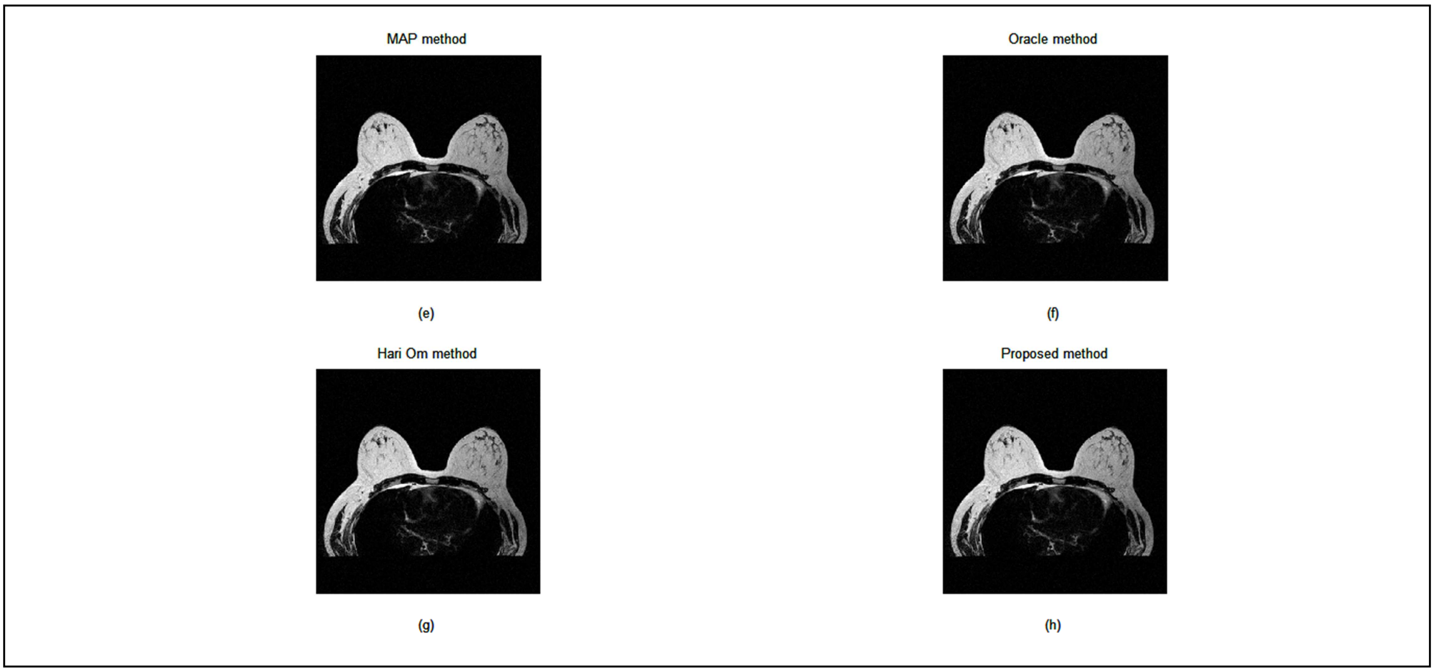

Figure 1 (e) MAP method (f) Oracle (g) Hari Om method (h) Proposed method, All processes performed at σ_n *=40.*

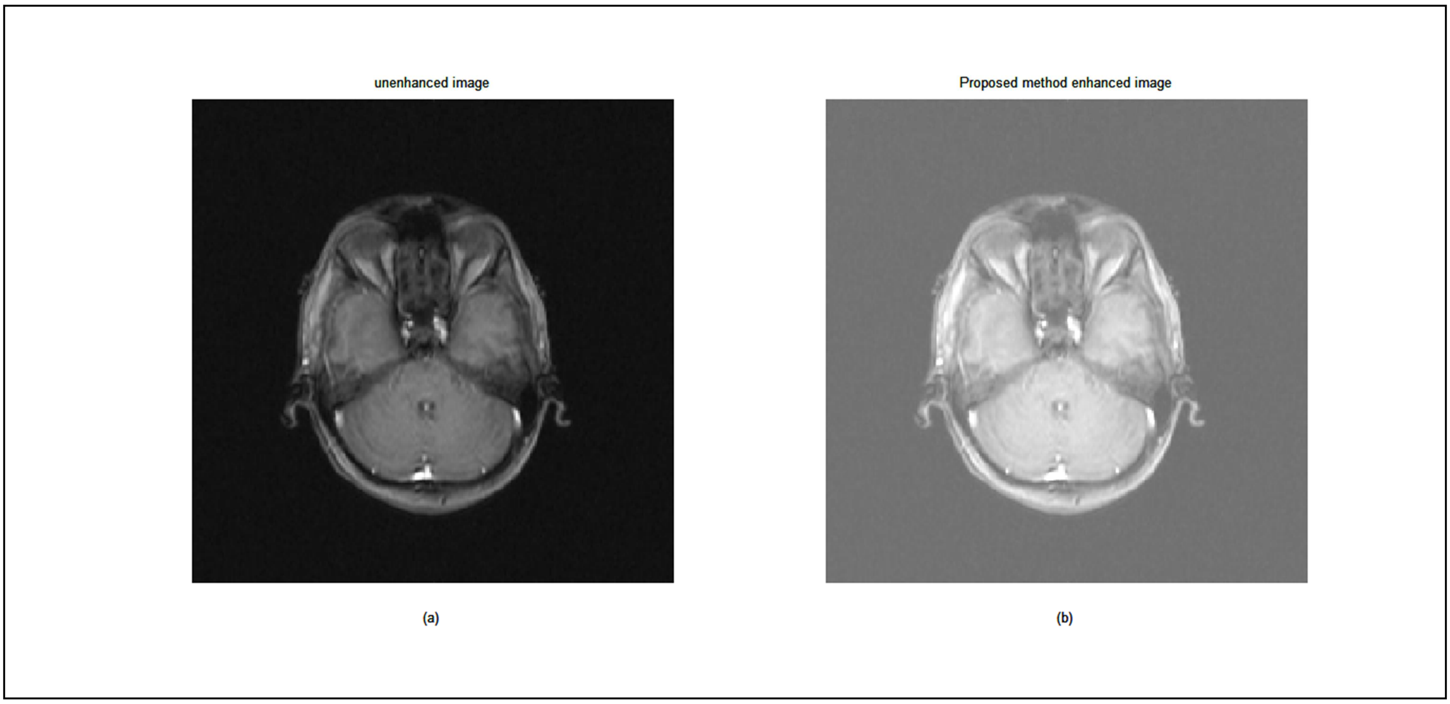

Figure 2 (a) Unenhanced Rembrandt-1 image (b) Enhanced Rembrandt-1 image using proposed method

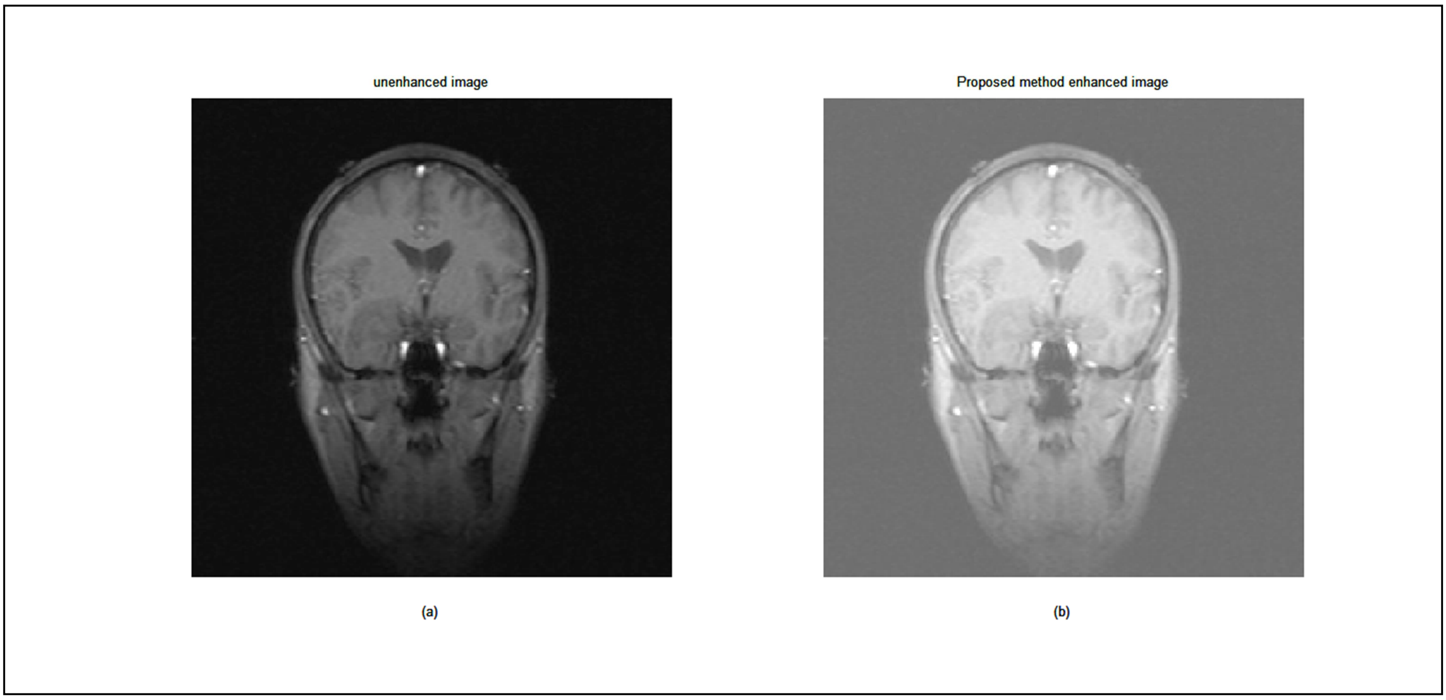

Figure 3 (a) Unenhanced Rembrandt-2 image (b) Enhanced Rembrandt-2 image using proposed method

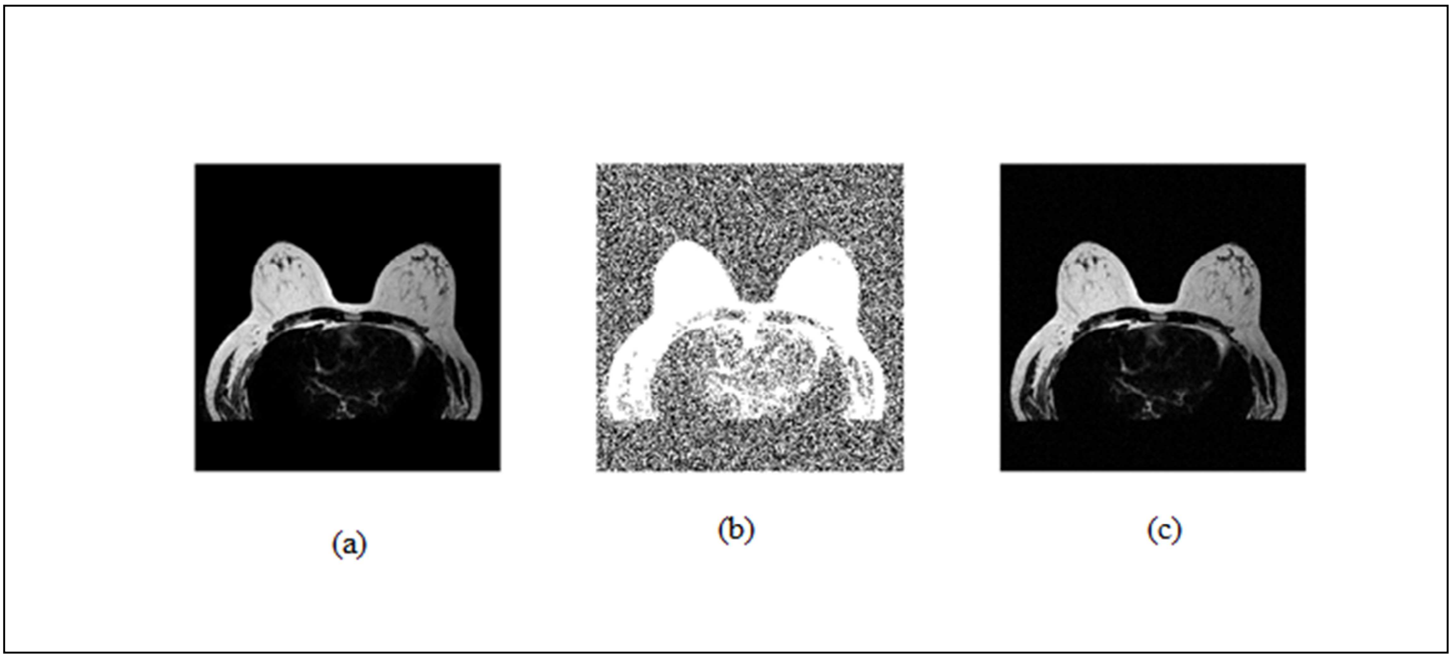

Figure 4 (a) Original image (b) Poisson-Gaussian noise under scaled image (c) Denoised image using proposed method

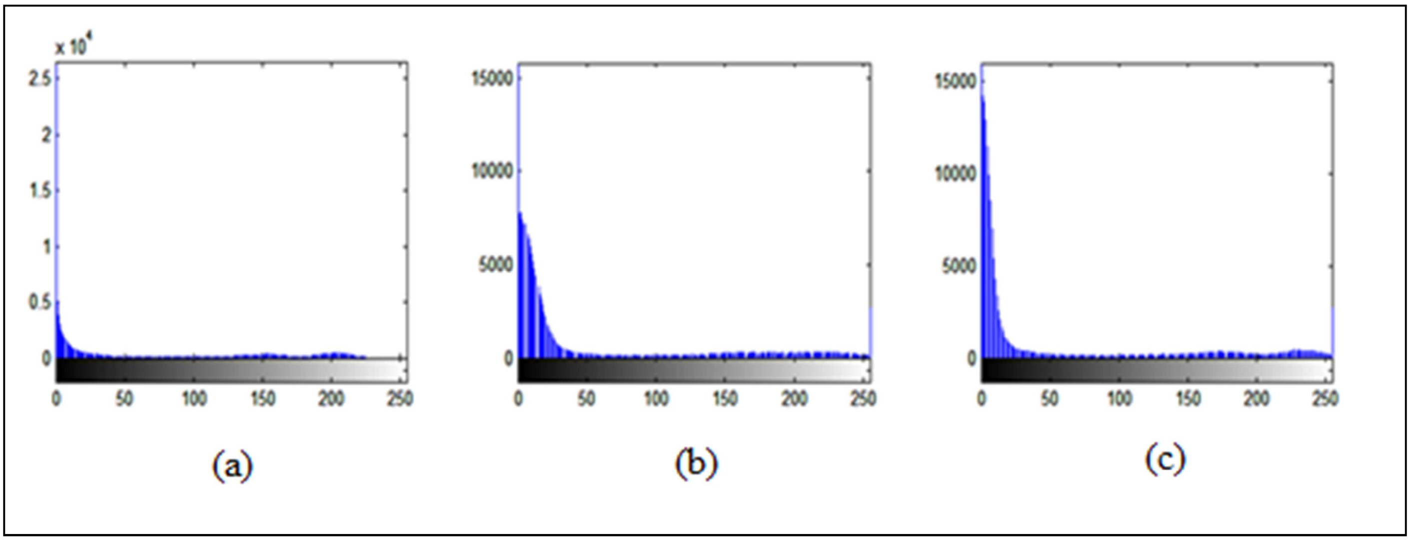

Figure 5 (a) Histogram of original image (b) Histogram of Poisson-Gaussian noise image (c) Histogram of Denoised image using proposed method

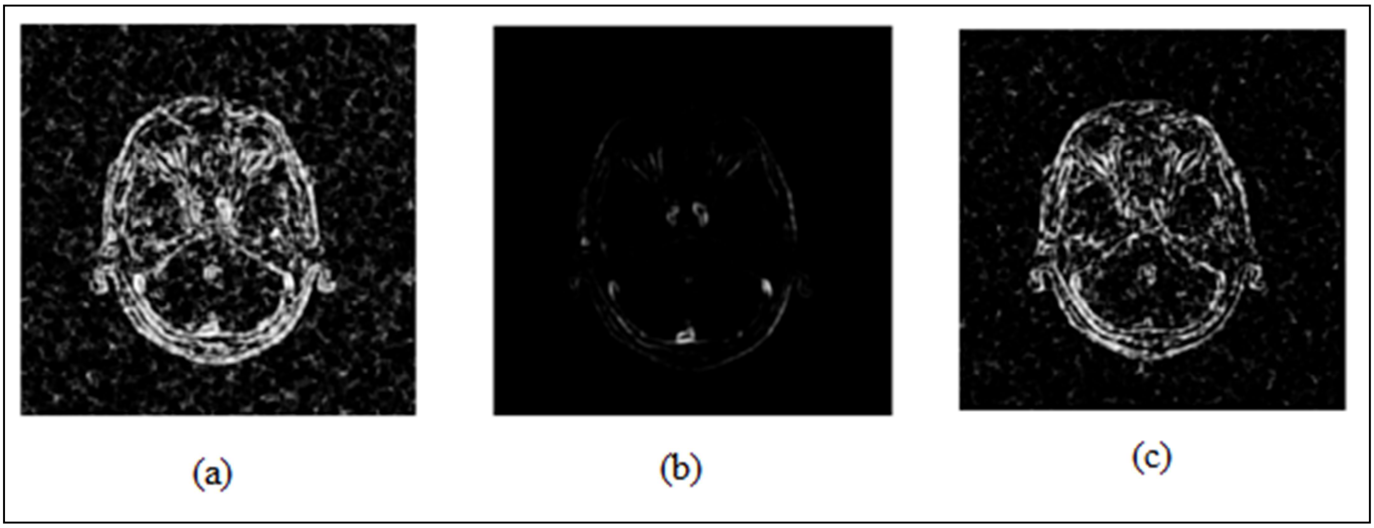

Figure 6 (a) SSIM map using Boyat_Joshi method without WPT + Bivariate Shrink if Standard deviation is 40; (b) SSIM map using Noisy image if Standard deviation is 40 and (c) SSIM map using WPT + Bivariate Shrink if Standard deviationis 40

2. Conclusion

Hence proposed filter is central point in digital image processing applications and necessarily necessary had been derived the steps to design quality denoising. In our approach Multi wavelet transforms are in use contemporaneously, and such a transform approximated in wavelet packet is perfectly. We employed a dual tree wavelet packet transform using Bivariate-Bayesian threshold which has shown advance features like shift invariance and directionality, as well as providing frequency resolution. Our method was worked with parameter estimation equations such as β and σ_x is subjected to quantify the local characteristics of sub-band. The simulation was confirmed that approximate 06dB improvement in PSNR values and approximate 6dB downfall in MSE values were measured.

3. References

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