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MRI MEDICAL IMAGE DENOISING BY COMBINED SPECTRAL SUBTRACTION AND WAVELET BASED METHODS

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ABSTRACT

Image denoising is a compromise between the removal of the largest possible amount of noise and the preservation of signal integrity and image resolution. To address this issue, a new hybrid approach is proposed by fusing dual band spectral subtraction and wavelet packet based thresholding method. The dual band spectral subtraction method (SS) is used for preprocessing of noisy MRI images in order to initially reduce the noise level and further the quality of images is improved by wavelet packet based thresholding method. Here threshold value is determined by Stein's Unbiased Risk Estimator (SURE) and three kinds of thresholding are considered for denoising. According to the computer simulation, the best method of threshold process is obtained by comparing the performance of three wavelet threshold selection rules that are applied to enhance the images. It is suggested from the experimental results that the proposed scheme gives an improved performance, which reflects in better image quality in all types of noisy environment. This approach is incorporated with spatial domain and frequency domain analysis. Results are measured objectively by Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Universal Quality Index (UQI) and subjectively by measuring the visual quality with Picture Quality Scale (PQS).Overall results indicate that the enhancement quality is performing well in proposed method.

Keywords: index terms—wavelet, image denoising, discrete wavelet, transform.

1. INTRODUCTION

Image denoising has become an essential exercise in medical imaging especially the Magnetic Resonance Imaging (MRI). In recent years, technological development has significantly improved in analyzing medical images. Medical image enhancement technologies have attracted much attention during the diagnosis process. Enhanced medical images are desired by a surgeon to help diagnosis and interpretation because medical image qualities are often deteriorated by artifacts. Nowadays Medical imaging is the best techniques for monitoring the person's diagnosis process. Most of the diseases are diagnosed by doctors using medical imaging methods. One problem that physician encounter is because of the low quality of medical image. This low quality causes difficulty during the diagnosis. So it is necessary to improve the quality of the medical image. Traditionally image enhancement is achieved by the use of linear processing techniques such as wiener filtering, median filtering, guassian filtering, etc[1].Inherently noise removal from image introduces blurring in many cases.

In the recent years there has been a fair amount of research on wavelet thresholding and threshold selection for image de-noising [2], [3],[4] because wavelet provides an appropriate basis for separating noisy signal from the original image signal. The motivation is that as the wavelet transform is good at energy compaction, the small coefficients are more likely due to noise and large coefficient due to important signal features. These small coefficients can be thresholded without affecting the significant features of the image. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, then it is set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential image characteristics and with less noise. In this paper, a near optimal threshold estimation technique for image denoising is proposed which is subband dependent i.e. the parameters for computing the threshold are estimated from the observed data,and one set for each subband.

2. WAVELET PACKET DECOMPOSITION

Wavelet transform is one of the promising methods of image denoising. The basic measure of the performance of a denoising algorithm is the quality of image and peak signal to noise ratio, which is defined by the ratio between original image and denoised image. The conventional wavelet transform decomposes only the low frequency components to obtain the next level's approximation and detail components; the current level of the detail components remains intact [5]. Wavelet packets, on the other hand, decompose both the approximation and the detail components of multiple levels. This results in more components representing the images and provides more flexibility, which makes the improvement in noise reduction and image quality. Wavelet packet decomposition results in a balanced binary tree structure as shown in "Figure-1". Subsequent levels in the tree are constructed by recursively applying the wavelet transform step to the low and high pass filter results from the previous wavelet transform step. Similarly the inverse

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wavelet packet can reconstruct the original image from the wavelet packet decomposition spectrum. Daubechies 14 tap wavelet has been chosen for this implementation.

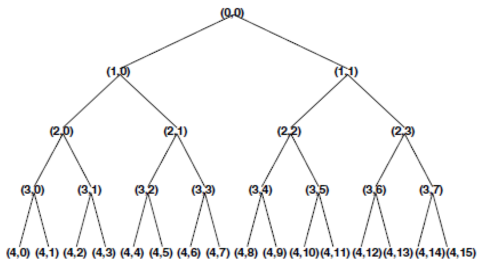

Figure-1. A Discrete Wavelet Packet Transform.

3. PROPOSED METHOD

The proposed SSWPT system structure is shown in "Figure-2". In order to initially reduce the noise level, the noisy image is first preprocessed with spectral subtraction routine, containing four stages. In the first stage, the given image is windowed and the magnitude spectrum is estimated using the FFT. In the second stage, split the noise and image spectra into different frequency bands and calculate the over-subtraction factor for each band. The third stage includes processing the individual frequency bands by subtracting the corresponding noise spectrum from the noisy image spectrum. Lastly, the modified frequency bands are recombined and the original signal is obtained by using the noisy phase information and taking the IFFT in the fourth stage. The effect of image conditioning operations is to neutralize the distortion in the spectral content of the input data due to the analysis window and to precondition the input data to surmount the distortion due to errors in the subtraction process.

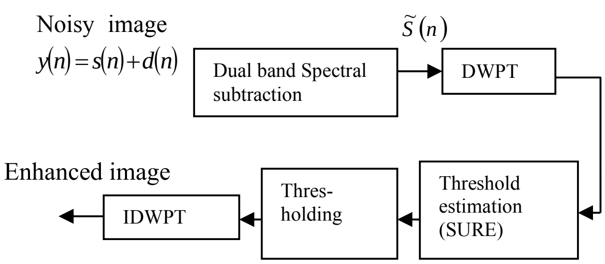

Figure-2. Proposed scheme.

Assuming the noise to be uncorrelated with the clean image signal, the resulting input corrupted image can be expressed as,

$$y(n) = s(n) + d(n) \tag{1}$$

The estimate of the clean speech spectrum in the i th band is obtained by ,

$$\left|\hat{S}_i(k)\right|^2 = \left|\bar{Y}_i(k)\right|^2 - \alpha_i\, \delta_i \left|\hat{D}_i(k)\right|^2 \qquad b_i \le k \le e_i \;\; ,i=1,2 \tag{2}$$

where b_i and e_i are the beginning and ending frequency bins of the i th frequency band, δ_i is an additional band-subtraction factor that can be individually set for each frequency band to customize the noise removal process and α_i is band specific over subtraction factor.

Noise estimation plays an important role in this method of image enhancement. For an efficient noise estimation algorithm the resultant signal estimation will have great accuracy. The algorithm used for noise estimation in this work is based on the estimate of power spectral density of noise. But, the noise estimate is updated continuously in every frame. This is based on the concept that the power spectrum of image was both localized in spatial domain and in frequency [6], [7]. The noise spectrum estimate is updated using the following recursive equation

$$D(\alpha,k) = \delta_s(\alpha,k)\;\; D(\alpha-1,k) + (1-\delta_s(\alpha,k)\;\; \left|Y(\alpha,k)\;\right|^2 \tag{3}$$

Where D (α, k) is the estimate of the noise power spectrum and δ (α, k) is the frequency dependent smoothing factor.

A three level wavelet packet transform is then applied to decompose the pre-processed signal into sub bands. To account for Cartesian MRI and correlated noise, thresholds are independently estimated for each time frame and wavelet decomposition sub band. This is further refined using a suitable thresholding approach based on a SURE risk rule [8].Finally, the inverse wavelet packet transform synthesizes the enhanced speech.

4. DENOISING BY WAVELET PACKET THRESHOLDING

A generalization of the discrete wavelet transform is the discrete wavelet packet transforms (DWPT) which keeps splitting both low pass and high pass sub-bands at all scales in the filter bank implementation, thus Wavelet Packet obtains a flexible and a detail analysis transform. So the Wavelet Packet transform is used for de-noising. The main steps of image denoising are:

- Wavelet packet transform of pre estimated image.
- Shrinkage of the empirical wavelet coefficients.
- Inverse wavelet packet transform of the modified coefficients.

The denoising procedure requires the estimation of the noise level. In this work Stein's Unbiased Estimate of Risk (SURE) has been chosen as a principle for selecting a threshold to be used for denoising. SURE is an adaptive threshold selection rule. It is data driven. The aim of estimate is to minimize the risk. Because the coefficients of true signal are unknown, the true risk is also unknown. This technique calls for setting the level dependent threshold T to

$$T_{j,k} = \frac{Median(C_{j,k})}{0.6745}\sqrt{2\ln\left(N_{j,k}\log_2(N_{j,k})\right)} \tag{4}$$

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where $N_{j,k}$ is the number of the samples in the node (j,k) scale j and $C_{j,k}$ represents high frequency wavelet coefficients which are used to identify the noise components at j^{th} level decomposition and sub-band k in the wavelet packet tree.

5. THRESHOLDING ALGORITHMS

The thresholding parameter T is chosen with respect to the amount of noise in the input image. In general, the denoised solution is obtained using a single step of this multiscale procedure, i.e. the method is applied non iteratively. The specific choice of the wavelets and the shrinkage functions allows a large variability of wavelet shrinkage methods.

A. Soft shrinkage:

In which thresholding algorithm is defined as follow [9],[10].

$$Thr_{soft}(X,T)=\begin{cases}\operatorname{sgn}(X)\left(|X|-T\right) & |X|>T\\ 0 & |X|>T\end{cases} \tag{5}$$

B.Hard shrinkage:

Thresholding rule is given by [11] as follows

$$Thr_{hard}(X,T)=\begin{cases}X & |X|>T\\ 0 & |X|>T\end{cases} \tag{6}$$

In this algorithm has its own disadvantage in increasing the variance and impressing with little variations of the input samples.

C.Garotte shrinkage:

This algorithm is defined by using the following [12],

$$Thr_{Garrote}(X,T)=\begin{cases}0 & |X|\le T\\ \mathrm{X}-\dfrac{\mathrm{T}^2}{\mathrm{X}} & |X|>T\end{cases} \tag{7}$$

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed wavelet transform method has been implemented using MATLAB 7.10. The wavelet transform employs Daubechies'14 least asymmetric compactly supported wavelet with eight vanishing moments at four scales of decomposition. To assess the performance of SSWPT it is compared with some of the existing algorithm.

The performance analysis of image denoising techniques for MRI Brain cancer image having the dimension of about 300x300, corrupted by salt and pepper noise at 15dB is shown in "Figure-3". Spectral Subtraction removes the noises present at the edge of image, while Weiner Filter performs better than Median Filter. Comparative results are seen for SSWPT; thereby proposed method performs in a better manner than other.

"Figure-4" indicates the performance for MRI Brain image having the dimension of 342x390, for various image enhancement methods, corrupted by Gaussian noise. It is observed from the results that the proposed method is showing enhanced performance without affecting the originality of the image than the other existing methods even for higher decibel (dB) of noise level that is at 20dB

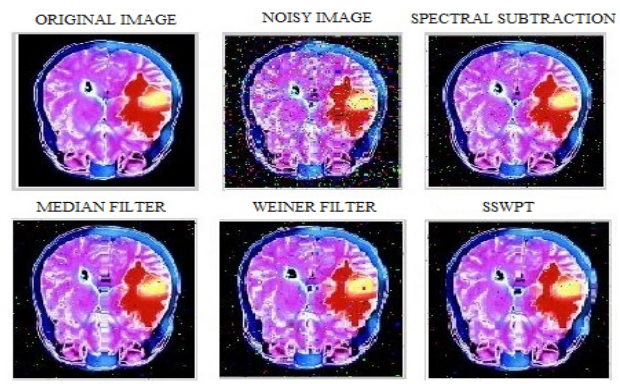

Figure-3. Performance analysis for MRI Brain cancer image.

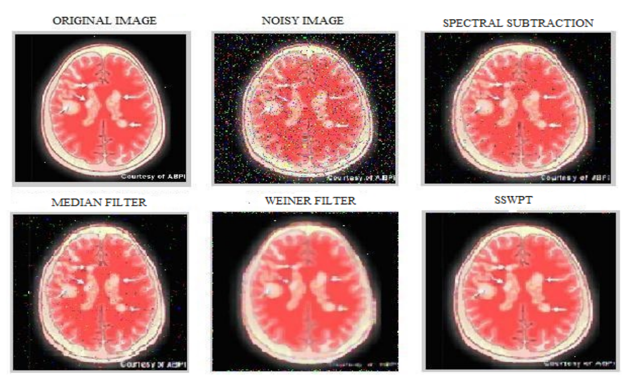

Figure-4. Performance analysis for MRI Brain image.

A. Objective measure Evaluation

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 a image enhancement algorithm.

1) PSNR and RMSE Ratio:

$$RMSE=\sqrt{\frac{\sum\left(f(i,j)-g(i,j)\right)^2}{mn}} \tag{8}$$

$$PSNR=20\log_{10}\left(\frac{255}{RMSE}\right) \tag{9}$$

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Here f (i,j) is the original medical image with impulse noise , g(i,j) is an enhanced image and m and n are the total number of pixels in the horizontal and the vertical dimensions of the image. The peak signal to noise ratio is denoted by PSNR and root mean square error value indicates RMSE measure.

2) Universal Quality Index (UQI):

It measures image similarity across distortion types. Distortions in UQI are measured as a combination of three factors; Loss of correlation, Luminance distortion and Contrast distortion. Let $\{x_i\}$ and $\{y_i\}$ =1, 2,...,N be the original and the test image and sigma value represents the variance. The UQI is given by

$$UQI = \frac{4\sigma_{xy}\bar{X}\bar{Y}}{\left[\sigma_x^2 + \sigma_x^2\right]\left[\left(\bar{X}\right)^2 + \left(\bar{Y}\right)^2\right]} \quad (10)$$

B. Subjective measure Evaluation

It is well known that the PSNR cannot faithfully indicate the image quality, especially for colored images. Thus subjective quality tests were performed by a group of 30 viewers with no previous familiarity with test material. Subjective distortion measures are based on the opinion of a group of viewers. Subjective measure can be done by comparing the image quality by getting people to view to the recorded image database. It is subjective in the sense that human listeners are known to grade the same image differently. This is perhaps the best method of evaluation if the enhanced image is intended for human eyes. The most commonly used subjective test is the picture quality scale (PQS) which is used to evaluate the user's acceptance of an image output system. For these listening tests, thirty subjects are surveyed and asked to rate the enhanced image for quality, edge detection, blurring effect etc., using a PQS scale.

"Figure-5" illustrates the PSNR performance for different denoising algorithms having the input noise level at 5dB for MRI brain image. It is observed that on an average SSWPT is performing well than WDT by 10.12% and Gaussian filter by 11.15% and median, Weiner filter by 13.45% and Spectral Subtraction by 15.57%.

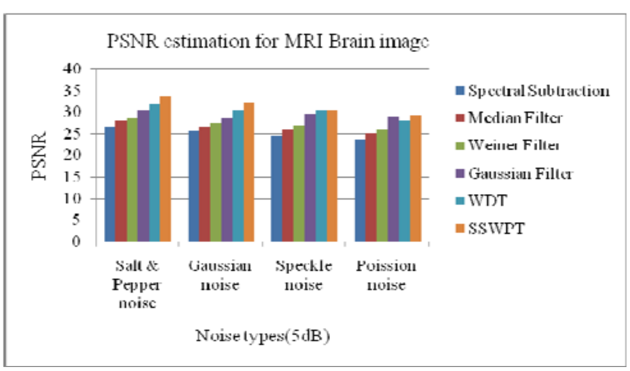

Figure-5. Performance of PSNR estimation for MRI Brain image.

"Figure-6".indicates the RMSE performance for an input noise level of 5dB.It shows that minimum error value is found for proposed technique and the highest error value is obtained for Weiner filter while removing Poisson noise. The error value looks in a similar manner for WDT method while removing the Speckle and Poisson noise.

It is inferred from the "Figure-7".that the image similarity between the original image and processed image is found to better enhanced in SSWPT than the existing algorithms. Poor image quality is obtained for median filter while removing salt and pepper noise, Gaussian noise and Speckle noise.

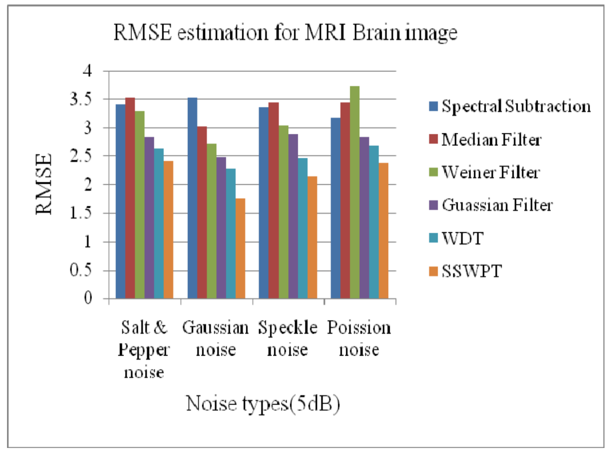

Figure-6. Performance of RMSE estimation for MRI Brain image.

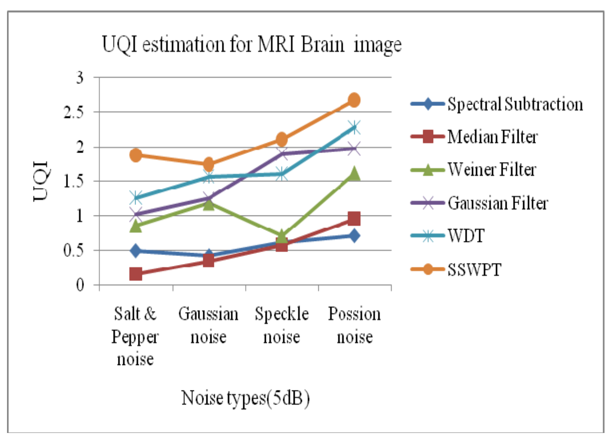

Figure-7. Performance of UQI estimation for MRI Brain image.

The variation in each viewer's score is indicated in "Figure-8".The quality of processed image is having the good score than WDT by 15.34% and Spectral Subtraction by 27.23%.It is also seen that Weiner filter and SSWPT is having the same score for Poisson noise.

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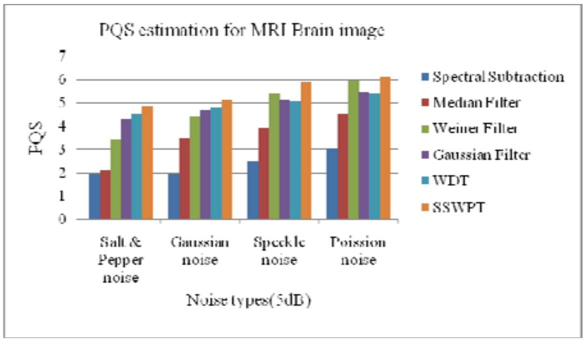

Figure-8. Performance of PQS estimation for MRI Brain image.

"Figure-9" illustrates the PSNR estimation for Salt and Pepper noise at different dB levels for MRI brain cancer image. It is seen that SSWPT shows an enhanced performance for all input noise level, next to SSWPT WDT shows good performance. At lower input noise level, the enhancement of Weiner and median filter goes in hand.

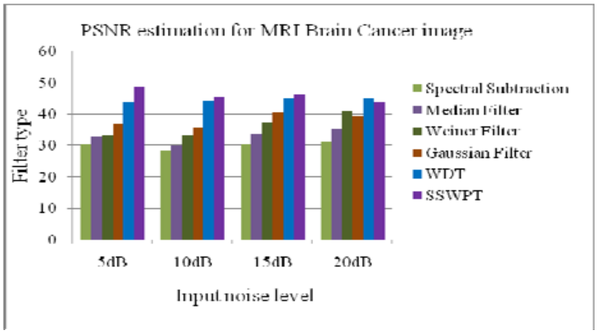

Figure-9. Performance of PSNR estimation for MRI Brain Cancer image.

The mean square error value for MRI brain cancer image at different noise level for Gaussian noise is predicted in "Figure-10". It is observed that minimum error value between processed image and the noisy image is found while applying the proposed technique and highest error value is rated for Spectral Subtraction and median filter at all level of noises.

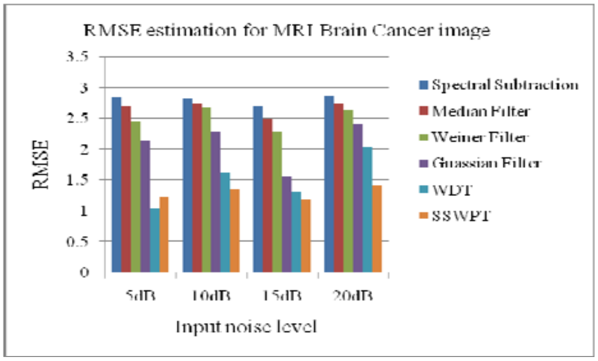

Figure-10. Performance of RMSE estimation for MRI Brain Cancer image.

The universal quality index measurement for Speckle noise at different noise levels ranging from 5dB to 20dB for MRI brain cancer image is shown in "Figure-11".Gaussian filter, median filter and spectral subtraction methods shows the linear increase. Better quality image is seen for proposed method.

Subjective quality measure like picture quality scale is rated for Poisson noise at different noise levels for MRI brain cancer image is depicted in "Figure-12".The score for SSWPT method is higher than WDT by 16.21% and 18.11% than Gaussian filter and 20.45% than Weiner filter and 23.22% than median filter and 25.67% than spectral subtraction method at various dB levels

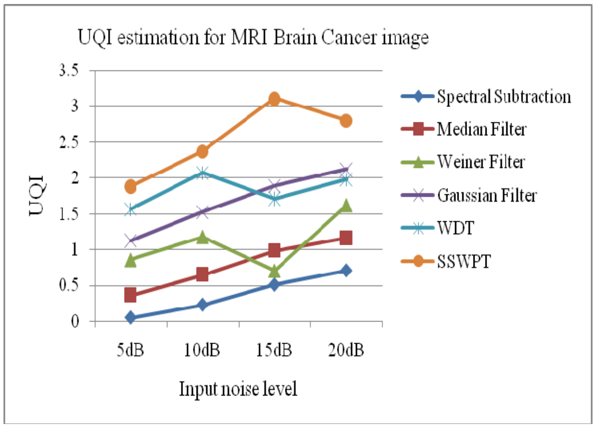

Figure-11. Performance of UQI estimation for MRI Brain Cancer image.

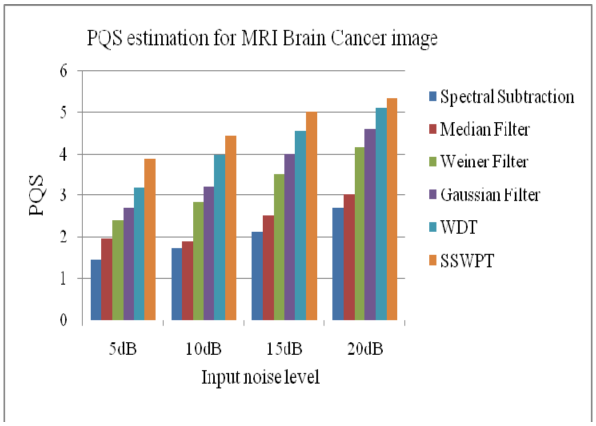

Figure-12. Performance of PQS estimation for MRI Brain Cancer image.

"Table-1" indicates the performance measure (PSNR) for MRI brain image at different dB for all types of noises. It is observed that Garrote thresholding is proved to be better when compared to soft and hard thresholds while used along with wavelet packet decomposition. The value of PSNR is high when removing Poisson noise than other type of noises.

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Table-1. Performance of PSNR Estimation for MRI Brain Image.

Noise types	Input noise level	Thresholding Algorithm		
		WPTS	WPTH	WPTG
Salt & pepper	5dB	25.13	26.32	27.22
	10dB	25.71	26.88	27.53
	15dB	26.10	26.97	27.84
	20dB	26.58	27.27	28.11
Gaussian	5dB	26.26	26.78	27.13
	10dB	26.47	26.95	27.38
	15dB	26.75	27.48	27.79
	20dB	27.07	27.83	28.52
Speckle	5dB	26.63	27.22	27.83
	10dB	27.22	27.19	27.72
	15dB	28.17	28.06	28.37
	20dB	28.25	28.61	30.22
Poission	5dB	29.51	29.72	29.86
	10dB	30.14	30.52	30.84
	15dB	30.44	31.00	31.62
	20dB	31.21	31.73	32.10

"Table-2" indicates the mean square error (RMSE) for MRI brain cancer image at different dB for all types of noises. It is seen that minimum error value is found while using Garrote threshold in wavelet packet decomposition when compared to other thresholding algorithms.

Table-2. Performance of RMSE Estimation for MRI Brain Image.

Noise types	Input noise level	Thresholding Algorithm		
		WPTS	WPTH	WPTG
Salt & pepper	5dB	3.21	3.01	2.86
	10dB	3.18	2.87	2.55
	15dB	3.02	2.66	2.27
	20dB	3.16	2.35	1.85
Gaussian	5dB	3.45	3.45	3.02
	10dB	3.03	3.72	2.71
	15dB	2.89	2.84	2.48
	20dB	2.46	2.67	2.28
Speckle	5dB	2.13	2.28	1.56
	10dB	1.03	1.62	1.32
	15dB	1.24	1.34	1.18
	20dB	1.11	1.21	1.04
Poission	5dB	2.77	2.45	2.36
	10dB	2.57	2.31	2.27
	15dB	2.11	1.89	1.74
	20dB	1.85	1.60	1.31

7. CONCLUSIONS

A combination of spectral subtraction and wavelet packet based image enhancement method using different shrinkage algorithm for denoising image from different noisy conditions at different dB levels(from 5dB to 20dB) has been presented. Enhancement results demonstrate that the wavelet packet transform with Garotte thresholding is performing better than other thresholding techniques. So in the proposed method, spectral subtraction is combined with wavelet packet transform along with Garotte thresholding. The quality and intelligibility tests were proved that the enhanced image and original image have better similarities on spatial domain analysis when compared to other exsisting algorithms like wavelet decomposition,Gaussian filter,median filter,Wiener filter and spectral subtraction.On an average the proposed technique is performing better than wavelet decomposition by 14.23% and Gaussian filter by 16.34% and median filter by 17.25% and Weiner filter by 18.21% and spectral subtraction by 18.81% at noise level ranging from 5dB to 20dB

We conclude that the competency of the proposed system to extract a clear and intelligible image from various adverse noisy environments in comparison with other well-known existing methods has been demonstrated through both objective and subjective measurements and it was well suited to enhance the image even for very strong noise condition and there by maintaining the image clarity and preserving the edge components.

The future work includes the fusion of thresholding for wavelet denoising even at (negative dB noise levels) which may be suitable for noise dominated image conditions yeilding further more better performance and its implementation can be used as a initial stage for segmenting the medical images for detection of abnormalities.

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