Despeckling of Medical Ultrasound Images Using Suitable Denoising Algorithms

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Abstract - *Ultrasound images are normally affected by speckle noise. Speckle noise is a granular noise that inherently exists and degrades the quality of the medical images. Many filtering techniques are used for the removal of speckle noise in digital images. Most of the existing techniques use hard and soft thresholding functions for denoising the image in which the large value of threshold results in too many zero coefficients. So the useful information is removed along with the noisy data. In the proposed approach, a novel correlation threshold is found by combining first and second level of the detail subbands. To overcome the smoothening effect and to preserve the details of the image, an exponential thresholding function is proposed instead of hard and soft thresholding function. The exponential operator is used to set the noisy coefficients gradually to zero in order to increase the threshold zone up to a certain limit. The performance is evaluated and the results are compared. The results in the proposed method enhances the peak signal to noise ratio and preserves the details of an image.*

Keywords*: Speckle noise, Ultrasound medical images, exponential thresholding function, Correlation threshold, Stationary wavelet transform, PSNR, MSE, SSIM.*

1. INTRODUCTION

Medical images are affected by noise during capturing or transmission. There are many modalities of medical imaging, X-ray images are used for diagnosing the diseases in bones. It will not be useful for imaging the soft tissues. Magnetic Resonance Imaging (MRI) can be used for imaging the soft tissues [1]. But it is not suitable for imaging the movements and it will also attracted by the metals such as watch, jewelleries of the patients. So it is difficult to diagnose the diseases in moving tissues by MRI scans. Computer Tomography (CT) can be used for imaging, but the radiation from the scan causes the skin cancer [2].

Ultrasound (US) scanning can be used for soft tissue imaging because it is less expensive and there will less radiation comparing with other imaging. So the ultrasound imaging is most widely used. But the drawback of ultrasound imaging is the presence of speckle noise. Speckle noise is a multiplicative noise, i.e. it is in direct proportion to the local grey level in any area. The source of this noise is attributed to random interference between the coherent returns. Speckle is an undesirable interference effect occurring when two or more US waves interfere with each other .So it is necessary to denoise the image in order to improve the diagnostic accuracy.

Many despeckling filters are used for the removal of speckle noise in an image. Single and Multiscale methods are widely used. In the single scale methods, wiener filtering and median filtering are mostly used. These filters removes the useful informations along with the noise pixels.

Multiscale methods are applied for the images by the wavelet decomposition. This multiscale decomposition decomposes an image into detail subbands and approximation subbands.

In thresholding, the coefficients below threshold is considered as noise and are removed. The standard thresholding functions used are hard and soft thresholding. The drawback of above methods is that the useful information gets removed along with the noisy components in an image. So there will be higher smoothening of an image and necessary details that are required for diagnosis will also be lost.

To overcome the shortcomings of previous thresholding techniques, a new thresholding function based on an exponential operator [6] is used in this paper. This exponential thresholding function preserves the details of an image by processing the noisy coefficients of an image. By increasing thresholding zone, the signal details can be preserved. Thus the essential informations required for diagnosis is preserved.

A new threshold is used in this paper by determining the correlation between the various levels of the horizontal, vertical and diagonal subbands. In this correlation threshold, if the coefficients has the signal components then threshold will be higher. The threshold value will be lower when the coefficients are noisy. Hence the noisy coefficients are removed effectively and the details of an image are preserved comparing to the existing methods.

2. WAVELET THRESHOLDING

Wavelet threshold denoising is used for removing the noise present in the image while preserving the details of an image. Wavelet thresholding performs in various steps (1) Noisy image is decomposed into detail and approximation subbands by using wavelet transform (2). The noisy signals in the detail subbands coefficients are filtered by applying the thresholding function. (3) The denoised coefficients are reconstructed by applying inverse wavelet transform.

2.1. WAVELET SHRINKAGE DENOISING

In wavelet based denoising, the threshold is used to separate the wavelet coefficients into signal components and noisy components. The coefficients below the threshold are highly dominated by noise. The thresholding functions [3] are used for denoising the coefficients by replacing noisy coefficients (small coefficients below a certain threshold value) by zero [5].

2.1.1. HARD THRESHOLDING

In hard thresholding, the coefficients below threshold is considered as noise and are completely removed. Then value above threshold is considered as signal coefficients and these are kept unchanged. Hard thresholding equations are given below.

$$\hat{W}_{j,k} = \begin{cases} W_{j,k}, & |W_{j,k}| \geq T \\ 0\ , & |W_{j,k}| < T \end{cases} \quad (1)$$

Where, T is the threshold value and then $W_{j,k}$ is the wavelet subband coefficients. The drawback of the hard thresholding is that the useful information gets removed along with the noisy pixels in an image. So that there will be higher smoothening of an image

2.1.2. SOFT THRESHOLDING

In soft thresholding function, the value below threshold is made as zero completely and the value above threshold is denoised by using the equation given below.

$$\hat{W}_{j,k} = \begin{cases} 0, & |W_{j,k}| < T \\ \operatorname{sgn}(W_{j,k})\,(|W_{j,k}| - T), & |W_{j,k}| \geq \mathrm{T} \end{cases} \quad (2)$$

Where, T is the threshold value and then $W_{j,k}$ is the wavelet subband coefficients. In the above thresholding the signal components are processed and then noisy components (below threshold) gets removed completely. This also provides higher smoothing of an image.

2.2. PROPOSED THRESHOLDING ALGORITHM

The proposed approach uses an exponential thresholding function. Here, the noisy coefficients below the threshold are not completely made zero, instead the threshold zone is increased to set the wavelet coefficients gradually to zero [6] as shown in figure 1. The exponential thresholding equation is given by,

$$\hat{W}_{j,k} = \begin{cases} W_{j,k}.\exp\left(\mathrm{u}\,.\left(|W_{j,k}| - \mathrm{T_V}\right)\right), & |W_{j,k}| < \mathrm{T_v} \\ W_{j,k} & ,|W_{j,k}| \geq \mathrm{T_v} \end{cases} \quad (3)$$

Where, T is the threshold value, $T_v = v.T$ and then $W_{j,k}$ is the detail wavelet subband coefficients. The u and v are the positive constant values. Different values for u and v parameters have been tested. Then u= 2 and v = 2 have been chosen as optimum values. The proposed method offers an improvement in PSNR and edge preservation index.

2.3. THRESHOLDING PARAMETERS

Selection of threshold is a critical task in any denoising algorithm. A small threshold will give a result close to the input, but the result will be still noisy. A large threshold produces a signal with a large number of zero coefficients. This leads to a smooth signal. This destroys the necessary details of an image. Hence an optimal selection of threshold is necessary.

2.3.1. PROPOSED THRESHOLD

The correlation threshold is found by calculating the correlation between the adjacent levels of the subband. In this correlation threshold, if the signal components are present in the coefficients then the threshold will be higher. If the noisy components are in the coefficients then the threshold will be lower. The correlation between the levels of the three detail subbands are calculated as given in equation (4).

$$C = |W_i * W_{i+1}| \quad (4)$$

Where i is the current decomposition level. W_i and W_{i+1} are wavelet coefficients of current level and next level detail subbands. The correlation is found for the two levels of three detail subbands. The maximum value of each row is calculated in horizontal direction of the correlation values of detail subbands of an image. Then the mean value of the maximum values obtained in horizontal direction is calculated for the three detail subbands and it is denoted as Mean_{max}. The obtained values are multiplied with 0.8 and is given by

$$T_c = 0.8 * \text{Mean}_{max} \quad (5)$$

The value greater than T_c is considered as signal data and then they are kept unchanged. The coefficient values below threshold are considered as noise and are processed as given in equation (3). The value of 0.8 is obtained experimentally. The flowchart for the determination of correlation threshold is shown in the figure 2.

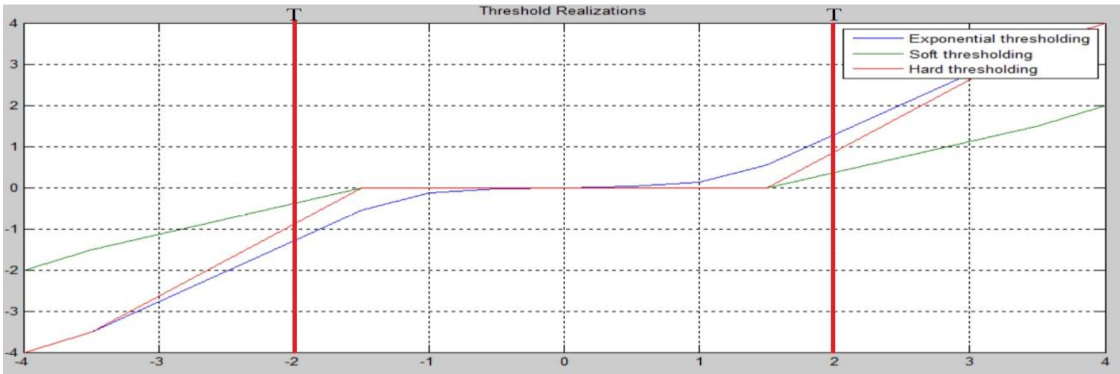


Figure 1. Comparison of thresholding functions

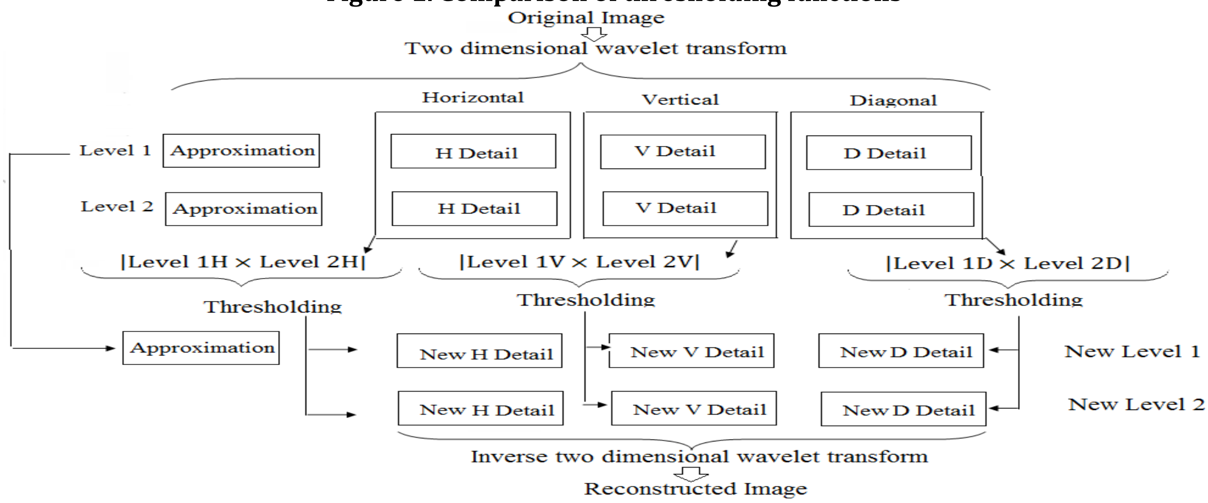


Figure 2. Flow chart for the determination of correlation threshold process

2.4. ALGORITHM

Step 1: Noisy image is decomposed into detail and approximation subbands by applying stationary wavelet transform.

Step 2: The noise variance for L level decomposition is calculated by using the diagonal HH1 subband as shown in equation (6).

Step 3: The correlation threshold is found by calculating correlation between the coefficients of various levels of detail subbands using the equation.

Step 4: The detail sub-band coefficients are processed by using the Exponential thresholding function using equation (3). All the detail subbands such as horizontal, vertical and diagonal subbands are denoised by applying the exponential thresholding function.

Step 5: The denoised subband coefficients are reconstructed by using inverse wavelet transform.

3. RESULTS

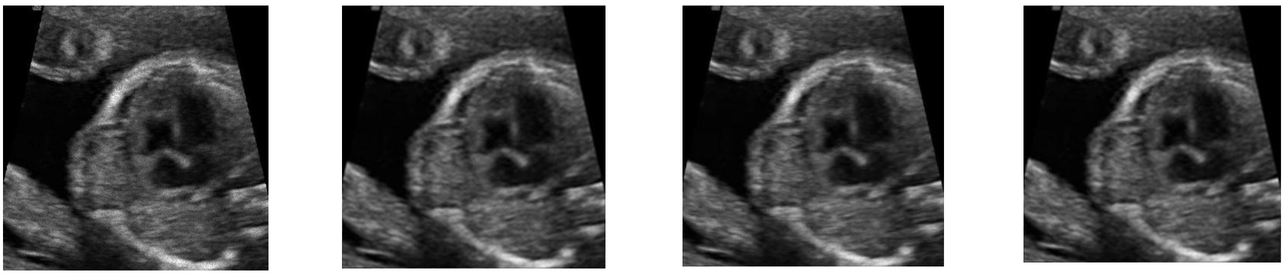
The experiment are conducted for different noise variances and their performance measures are calculated in terms of Peak Signal to Noise Ratio PSNR), Mean Square Error (MSE) and then the Structural Similarity Index Map (SSIM).

The performance of the proposed despeckling filter is tested with the ultrasound image of size 512*512 by adding the speckle noise with the variance 0.01, 0.04, 0.06, 0.08 and 0.1. The PSNR value and SSIM value of the proposed method is found to be improved is shown in the table 1 and MSE value gets decreased than the previous soft thresholding method is shown in table 1. The graphical analysis of comparison of PSNR, MSE and SSIM values of various depeckling filters are shown in figure 9-11.

Original ultrasound image is shown in figure 3. The Figure 4-8 shows that the visual quality of the denoised images for different noise variance. The noisy images for different variances are shown in (a) of figure 4-8.

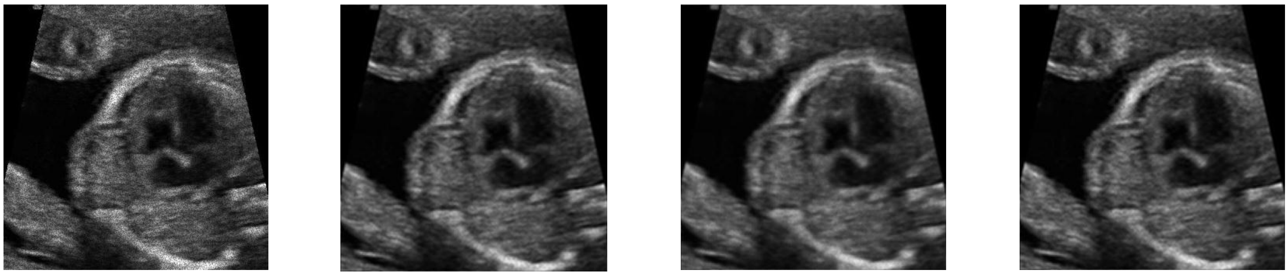
The denoised images of despeckling filters such as bayes shrink (b), exponential thresholding with bayes threshold (c) and exponential thresholding with correlation threshold (d) are shown in figure 4-8

Figure 3. Original Ultrasound image



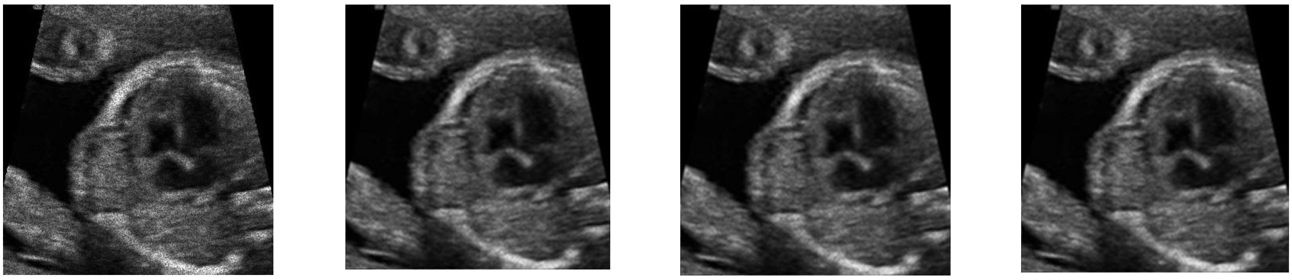
(a) (b) (c) (d)

Figure 4. Visual quality of Ultrasound image of noise variance 0.01



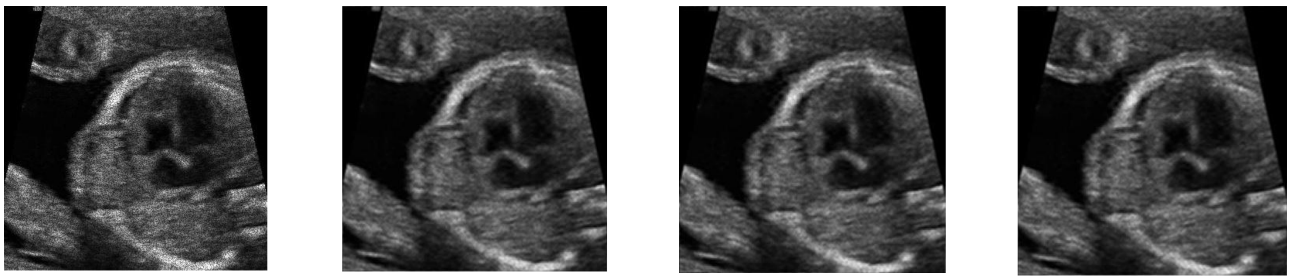
(a) (b) (c) (d)

Figure 5. Visual quality of Ultrasound image of noise variance 0.04



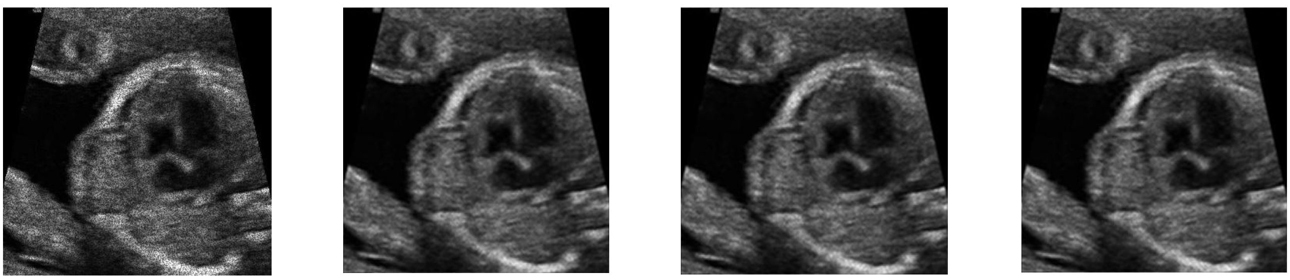
(a) (b) (c) (d)

Figure 6. Visual quality of Ultrasound image of noise variance 0.06



(a) (b) (c) (d)

Figure 7. Visual quality of Ultrasound image of noise variance 0.08



(a) (b) (c) (d)

Figure 8. Visual quality of Ultrasound image of noise variance 0.1

Table 1 .Comparison of performance measures for various denoising filters

NOISE VARIANCE	PERFORMANCE MEASURES	SOFT THRESHOLDING	EXPONENTIAL THRESHOLDING WITH BAYES THRESHOLD [7]	PROPOSED FILTER
0.01	PSNR	40.3112	40.4294	**40.5507**
	MSE	6.0529	6.0276	**5.7981**
	SSIM	0.9464	0.9504	**0.9586**
0.04	PSNR	38.4509	38.5074	**38.577**
	MSE	9.2894	9.1693	**9.0089**
	SSIM	0.9286	0.9297	**0.9373**
0.06	PSNR	37.5133	37.5796	**37.664**
	MSE	11.5279	11.3694	**11.2941**
	SSIM	0.9161	0.9173	**0.9178**
0.08	PSNR	36.8215	36.8448	**36.8292**
	MSE	13.5185	13.4463	**13.3946**
	SSIM	0.9056	0.9058	**0.9115**
0.1	PSNR	36.3305	36.4761	**36.5975**
	MSE	14.8377	14.7249	**14.7050**
	SSIM	0.8963	0.8971	**0.9027**

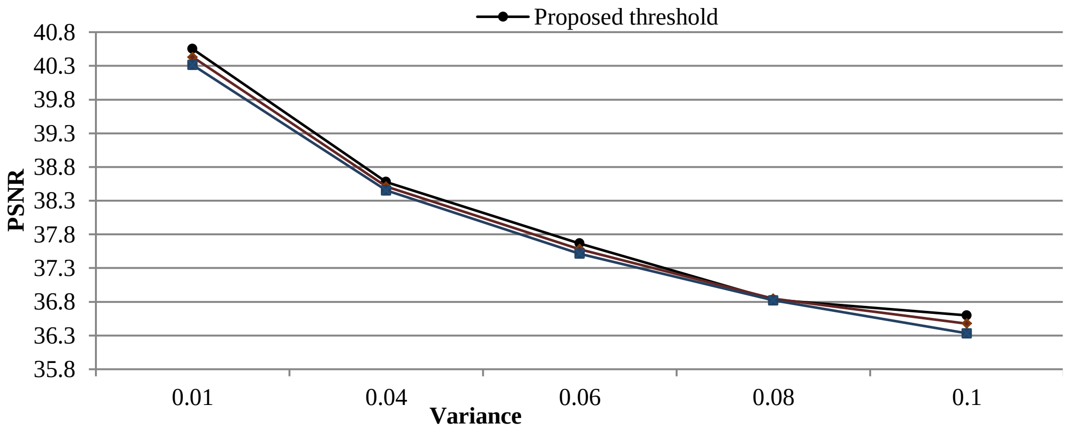


Figure 9. Graphical analysis of comparison of PSNR values for various denoising filters

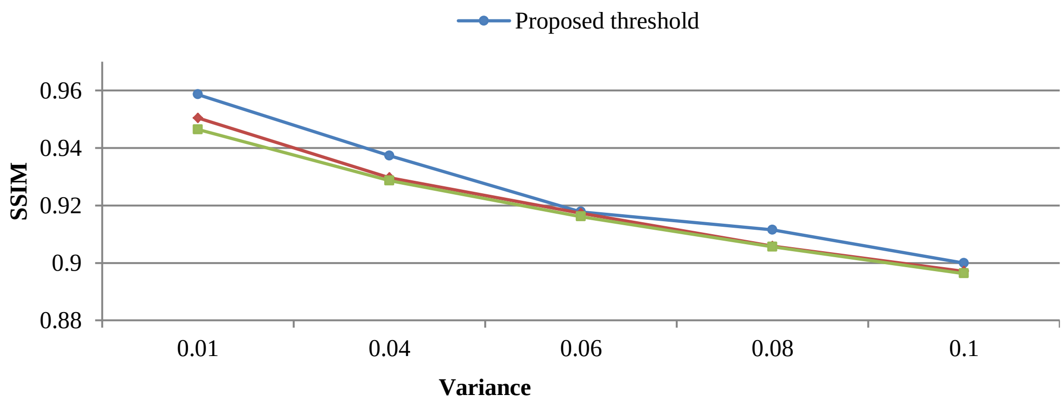


Figure 10. Graphical analysis of comparison of SSIM values for various denoising filters

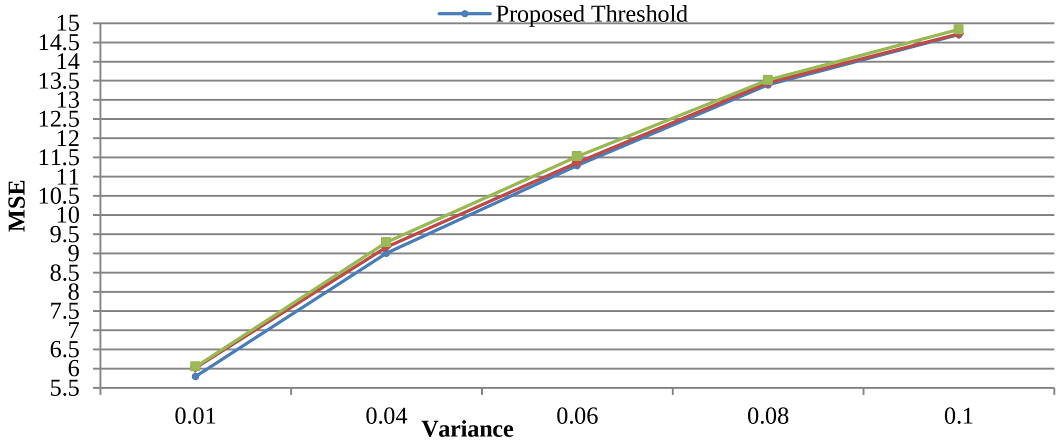


Figure 11. Graphical analysis of comparison of MSE values for various denoising filters

4. DISCUSSION

The multiresolution analysis of an image is done using stationary wavelet transform, to obtain the approximate and detail subbands. A new correlation threshold is proposed by combining the first and second level subbands coefficients.

An exponential thresholding function is used instead of hard and soft thresholding function. The exponential operator is used sets the noisy coefficients gradually to zero by increasing the threshold zone inorder to preserve important image details. The peak signal to noise ratio increases when both *u* and *v* parameters increase in exponential thresholding.

The performance is evaluated and are compared as shown in table1. The correlation based threshold applied with the exponential thresholding provides the further enhancement of the peak signal to noise ratio of about 0.30% for low noise variance and 0.33% for high variance and reduces mean square error of about 3.807% for low noise variance and 0.135% for high variance comparing with the exponential thresholding method. Thus the details of the denoised image is preserved and the quality of an image is improved than the existing techniques.

5. CONCLUSION

In this paper, a new correlation threshold based wavelet shrinkage with exponential thresholding function is proposed. By increasing the threshold zone, using exponential thresholding function and making use of the relation between wavelet coefficients of adjacent levels the denoising performance is found to be improved.

6. REFERENCE

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