A New Approach for Image Enhancement using Hybrid Threshold

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***Abstract*—Now a day's, image processing is an important task in many application and area ranging from television to tomography, from photography to publishing and many more. Out of various images processing technique, denoising is an important pre-processing task before further processing of images. The process in which noise signal is separated from meaningful signal to generate a noise free image is called denoising. The search for efficient image denoising methods is still a valid challenge at the crossing of functional analysis and statistics. In this paper, a new model based on the hybridization of visu shrink and sure shrink for denoising of variety of noisy images in wavelet domain is presented along with the standard thresholding techniques and a comparative analysis of proposed method with Bayes thresholding techniques has been carried out very effectively on the basis of PSNR, MSE and BER. The various noises consider during experiments are additive Gaussian noise, speckle noise and salt and pepper noise.**

***Keywords*— Visual Shrink, Sure Shrink, Bayes Shrink, Wavelet Thresholding, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Bit Error Rate (BER)**

I. INTRODUCTION

Denoising is a process of removal noise from the digital image to get a denoised image. Noise is unwanted signal that is added into image during acquisition, transmission & reception and storage & retrieval processes. As a result, there is degradation in visual quality of an image. To get a denoised image, it is necessary to remove the embedded noise from the image without disturbing the edges and other fine detailed features as much as possible [5]. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and cause blurring of the images. Different types of images inherit different types of noise and different denoised models are used. Denoising method tends to be problem specific and depends upon the type of image and noise. Donoho and Johnstone [1] pioneered the work on filtering of additive Gaussian noise using wavelet thresholding. In wavelet thresholding, image data is decomposed into wavelet coefficients, comparing these coefficients with a given threshold value and shrinking these coefficient close to zero to remove the effect of noise in the data. The image is reconstructed from the modified coefficients. Denoising of image using wavelet technique is very effective because of its multiresolution and sparsity characteristics. It is good at energy compaction, the small coefficients are due to noise and large coefficients are due to important signal feature. Due to this fact noise can be effectively removed from image data. Donoho and Johnstone proposed two methods based on wavelet thresholding; one is VisuShrink based on universal threshold and second is SureShrink based on adaptive threshold [2]. Chang, Yu and Vetterli proposed BayesShrink to minimize the Bayesian risk [3]. In our proposed method, we hybrid universal threshold and adaptive threshold and compare it with Bayes shrink. The rest of the paper is organized as follows. Section 2 describes the related work. Section 3 discusses the proposed work. The experimental results are given in Section 4. The results are discussed by taking three test images and various noise levels. Finally, the concluding remarks are given in Section 5.

II. RELATED WORK

This section describes Visual Shrink, Sure Shrink and Bayes shrink with its advantages and disadvantages.

A. Visual Shrink

VisuShrink was introduced by Donoho [1]. It uses a threshold value t that is proportional to the standard deviation of the noise. It follows the hard thresholding rule. It is also referred to as universal threshold and is defined as

$$t = \sigma\sqrt{2\log n}$$

σ^2 is the noise variance present in the signal and n represents the signal size or number of samples. An estimate of the noise level σ was defined based on the median absolute deviation given by

$$\hat{\sigma} = \frac{median\left(\left\{\left|g_{j-1,k}\right| : k = 0,1,\ldots,2^{j-1}-1\right\}\right)}{0.6745}$$

Where $g_{j-i,k}$ corresponds to the detail coefficients in the wavelet transform. Visu Shrink does not deal with minimizing the mean squared error. However, image reconstructed using Visu Shrink is smoothed. This is because Visu Shrink removes too many coefficients due to universal threshold. Visu Shrink follows the global thresholding scheme where there is a single value of threshold which is applied globally to all the wavelet coefficients.

B. Sure Shrink

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone and is called as SureShrink [2]. It is a combination of the universal threshold and the SURE threshold. In this method, a different threshold value t_j is calculated for each subband j in the wavelet transform which is referred to as adaptive thresholding and subband dependent thresholding. The goal of SureShrink is to minimize the mean squared error, defined as

$$mse = \frac{1}{n^2} \sum_{x,y=1}^{n} (z(x,y) - s(x,y))^2$$

Where $z(x,y)$ is the estimate of the signal while $s(x,y)$ is the original signal without noise and n is the size of the signal. SureShrink suppresses noise by thresholding the empirical wavelet coefficients. The SureShrink threshold $t*$ is defined as

$$t^* = \min(t, \sigma\sqrt{2\log n})$$

Where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance, and n is the size of the image. It apply threshold which one is minimum either it is t or universal threshold. SureShrink follows the soft thresholding rule. The thresholding employed here is adaptive.

C. Bayes Shrink

BayesShrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and it is also subband-dependent, which means that thresholding is calculated at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. The Bayes threshold, t_B, is defined as

$$t_B = \sigma^2 / \sigma_s$$

where σ^2 is the noise variance and σ_s^2 is the signal variance without noise. The noise variance σ^2 is estimated from the subband HH1 by the median estimator. BayesShrink performs better than SureShrink in terms of MSE. The reconstruction using BayesShrink is smoother and more visually appealing than one obtained using SureShrink [3].

The choice of a threshold is an important point of interest. It plays a major role in noise removal of images because denoising most frequently produces smoothed images, reducing their sharpness. Generally, the choice should be taken to preserve the edges of the denoised image [4]. Our proposed image denoising method is based on thresholding that not only removes noise but also preserves the edges. It is discussed in next section.

III. PROPOSED WORK

From the above mentioned method, Bayes shrink is better than visual and sure shrink. Visu shrink produces artifacts and remove only additive noise. It is not subband adaptive. Sure shrink is better than visu shrink but the reconstructed image is not so much smoother. As compare to both Bayes shrink give better result. The reconstruction using BayesShrink is smoother and more visually appealing than the one obtained using SureShrink.

Proposed method is the newly designed hybridized one as shown in figure 1. In this model a new hybrid method is developed based on previous ones. Hybrid means a thing made by combining two different elements. Same as meaning, hybrid threshold is developed. Hybrid threshold is a combination of Visu Shrink & Sure Shrink. Visu Shrink i.e. universal threshold or non-adaptive threshold and Sure Shrink i.e. adaptive threshold. In proposed method, first of all decomposition of noisy image is done at level 1, it gives four coefficient i.e. Approximation, Horizontal, Vertical & Diagonally. Approximation coefficient is kept aside and remaining three is threshold using universal threshold i.e. Visu Shrink. Universal threshold is calculated based on diagonal coefficient only and it apply to all three coefficients. After that approximate coefficient is decomposed upto given level and sure threshold is calculated using equations given in section 2 and apply to all coefficients one by one.

After wavelet thresholding step, inverse discreet wavelet transform is applied. First image is reconstructed from the coefficient which is threshold by Sure Shrink. Second final recovered image is constructed from the coefficient which is threshold by Visu Shrink and resultant coefficient of first step.

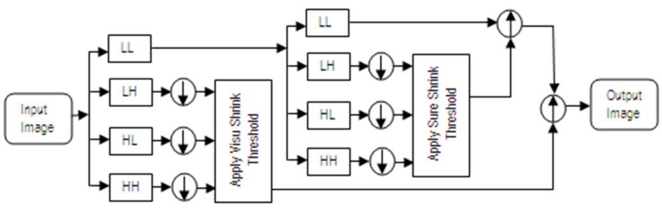

Fig. 1 The Proposed hybrid Model

IV. RESULT AND DISCUSSION

To see the qualitatively as well as quantitatively performance of the proposed algorithm, the experimental study has been performed on several RGB test images. In our experiments, we have used Symlet wavelet of length eight up to four decomposition levels is used. For each test images, three noisy versions were created by adding noise with sigma value 55, 65 and 75. The noise variance is estimated by using robust median estimator. The noisy images are denoised with both methods: *BayesShrink* and *Proposed Method*. The results are compared qualitatively (visually) as well as quantitatively using quality measures PSNR, MSE & BER. Figure 2 shows the original test images considered in our experiments each of size 512 × 512. The PSNR, MSE and BER values obtained for all the models considering all the images are given in table 1, table 2 and table 3 respectively. Table 1 shows the results of quality metrics on tulips.jpeg corrupted with Gaussian noise. Table 2 shows the results of quality metrics on penguin.jpeg corrupted with salt and pepper noise. Table 3 shows the results of quality metrics on mandrill.jpeg corrupted with speckle noise. Figure 3 shows tulips image corrupted with Gaussian noise, denoised with Bayes shrink and proposed method. Figure 4 shows Penguins image corrupted with Salt and Pepper noise denoised with Bayes shrink and proposed method. Figure 5 shows Mandrill image corrupted with Speckle noise, denoised with Bayes shrink and proposed method.

a b c

Fig. 2 Original RGB test images

From the mathematical and experimental results it can be concluded that overall proposed method gives better result than Bayes shrink. It outperforms when image is corrupted with Gaussian and salt and pepper noise but in case of speckle noise, PSNR value is higher than Bayes shrink but not so much improvement in visual quality. Resultant image is blurred as compared to Bayes shrink.

V. CONCLUSIONS

In this paper, we have discussed a hybrid image denoising method based on VISU shrink and SURE shrink thresholding methods. This proposed method removes the noise from the noisy image significantly. It has either better performance than or comparable in terms of PSNR, BER and MSE to the Bayes Shrink. From all the result shown in figures and tabulated in tables, it can be concluded that the proposed thresholding technique i.e. hybrid threshold, leads to fairly good results as far as denoising of RGB images is concerned as compared to Bayes shrink. In future, we try to extend this hybrid method with bilateral filter and normal shrink [6] [7].

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TABLE I

RESULTS OF QUALITY METRICS ON TULIPS.JPEG WITH GAUSSIAN NOISE

Sigma Value	**Bayes Method**			**Proposed Method**		
	MSE	**BER**	**PSNR**	**MSE**	**BER**	**PSNR**
55	92.7011	0.035137	28.46	57.5005	0.03275	30.5341
65	98.17	0.035447	28.211	65.5191	0.03337	29.9671
75	101.4747	0.035629	28.0672	70.4103	0.033722	29.6544

TABLE II

RESULTS OF QUALITY METRICS ON PENGUINS.JPEG WITH SALT AND PEPPER NOISE

Sigma Value	**Bayes Method**			**Proposed Method**		
	MSE	**BER**	**PSNR**	**MSE**	**BER**	**PSNR**
55	42.6109	0.031411	31.8356	32.2365	0.03026	33.0473
65	48.2228	0.031951	31.2983	34.8732	0.030576	32.7059

75	52.6578	0.032346	30.9162	37.0296	0.030821	32.4453

TABLE III
RESULTS OF QUALITY METRICS ON MANDRILL.JPEG WITH SPECKLE NOISE

Sigma Value	Bayes Method			Proposed Method		
	MSE	**BER**	**PSNR**	**MSE**	**BER**	**PSNR**
55	57.9259	0.032785	30.5021	54.1992	0.032477	30.7909
65	60.392	0.03298	30.321	54.3716	0.032492	30.7771
75	62.5847	0.03315	30.1661	54.1513	0.032473	30.7947

a b c

Fig. 3 (a) Noisy Image (b) Denoised with Bayes Shrink (c) Denoised with Proposed method

a b c

Fig. 4 (a) Noisy Image (b) Denoised with Bayes Shrink (c) Denoised with Proposed method

a b c

Fig. 5 (a) Noisy Image (b) Denoised with Bayes Shrink (c) Denoised with Proposed method