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Improved Image Denoising with the Integrated Model of Gaussian filter and Neighshrink SURE

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Abstract: Image denoising, being an important preprocessing stage in image processing, minimizes the noise interfering with the information content of the image. The denoising problems are addressed by various techniques starting from the Fourier transforms to wavelets. Because of the localized time frequency features and advantages of multi resolution capabilities, the wavelets have been extensively used in the denoising process. The development of algorithms for the wavelet thresholding or shrinkage strategies along with different filters have resulted in the betterment of image quality after the denoising. Even though the image denoising algorithm based on a combination of Gaussian and Bilateral filters, shows good performance but lacks in consistency with respect to the noise levels and also the type of images used. This paper discusses the advantages of NeighShrink SURE rule in developing an effective thresholding strategy, thereby proposing a improved denoising method incorporating the NeighShrink SURE rule along with combination of Gaussian filter model. The methodology employs the use of subband thresholding derived from the NeighShrink SURE rule. The outcome of the proposed method exhibits a comparatively improved performance in Peak Signal to Ratio (PSNR) and Image Quality Index (IQI) values of the test images.

Keywords : Image denoising; Gaussian filter; Wavelet thresholding; NeighShrink SURE

I. INTRODUCTION

The domain of image processing, at present covers a wide range applications involving, computer generated images, ultra sound images and electron microscopy etc., with the advancement in imaging systems that encompass almost the entire electromagnetic spectrum from gamma rays to radio waves[1]. Therefore, it is still a challenge for the researchers to find solutions to the practical problems associated in making the image useful and effective for the human perception.

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The unwanted signal that interferes in the image details due to various sources and reasons, called, "noise" is the main cause of disturbing the natural intensities of the pixels in the image.

The process of denoising, hence becomes an important preprocessing technique in the image processing domain. The denoising process takes the noisy image as the input and produces a denoised image by taking care of the natural details of the image. To preserve the image details after denoising, many researchers have proposed various techniques by incorporating spatial domain filters, frequency domain filters, wavelet based methods or even a hybrid kind of filters with ultimate goal of reducing the noise and enhance the image quality for visual inspection. The spatial methods work on every pixel of a given image, the process involves identifying a center point in the neighborhood of pixels in a small area, then applying the method to the selected pixels, result of the operation would become the response of that selected pixel or point and this the process is repeated throughout the image covering all the pixels and replacing all the selected pixel values with the result of the respective operation in all the neighborhoods [1]. This, simple to operate filter, removes high frequency noise and at the same time smoothens the edges [2] that are integral part of the image under test. This drawback of edge smoothening has been addressed in several studies with modification in the linear and nonlinear filtering techniques. The frequency domain techniques make use of the advantage of convolution that can be transformed as the multiplication of the spectra reducing the complexity to some extent. But the frequency domain filters run a low pass filter to secure the image details assumed to be in low frequency range but it becomes almost ineffective as it removes high frequency noise along with the desired high frequency image content. This process results in over smoothing and the image loses the visual quality. The significant contribution in the image denoising and related work has come from the studies using wavelets [3, 4]. The discrete wavelet transform (DWT) used for multiresolution images, provides the necessary information on the spatial and frequency characteristics. The noise reduction techniques using wavelet transform generally have the following procedure and a block representation given in Fig. 1.

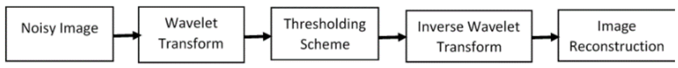

Fig.1 Wavelet based denoising process

Applying DWT on the noisy image, decomposes it into wavelet coefficients called, approximate and detail coefficients. The next step involves a logical decision making for modifying the detail coefficients based on a chosen thresholding/wavelet shrinkage function [5, 6].

A several statistical threshold methods called, “shrinkage schemes” are already in use to determine the optimal threshold value. A plenty of algorithms have been developed to improvise the performance of the denoising system by introducing a variety of shrinkage schemes, a few prominent ones are, VisuShrink, SUREShrink, BayesShrink and NeighShrink, etc. An efficient recursive process to choose distinct threshold value for each subband at each level of decomposition was proposed by Donoho [5] and it used adaptive thresholding mechanism. The limitation of this method is, its dependence on the estimation of statistics of the wavelet coefficients of the original image from that of corrupted image. The studies done by Chang et.al [8] introduced another strategy, assuming a generalized Gaussian distribution of wavelet coefficients called “BayesShrink” [8]. The blend of Gaussian filter with BayesShrink thresholding proposed by Shreyamshakumar [10] yielded a better results in terms of PSNR and IQI in comparison with various methods.

The organization of the paper is as follows; the section II describes the proposed denoising model, section III discusses the results obtained, section IV summarizes with a conclusion followed by a list of references.

II. PROPOSED DENOISING MODEL

A. Related Work and Theory

The linear filtering properties of the Gaussian filter removes high frequency noise and smoothens the image. The theory of the Gaussian filter illustrate the dependence of pixel intensity or a weight on its the distance [10] as given in (1),

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma 2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

The assumption followed in Gaussian filter design [17] is, that the images have smooth spatial variations and the pixels in the given neighborhood have similar intensities. But this assumption does not hold good at the edges of the images and hence blurred effect is created after the application of filter. This blurring effect is minimized by bilateral filter [11] which is a nonlinear filter that operates on the geometric closeness of the pixels and similarities in the intensity levels. The output of the filter [10] with respect to a pixel at point p is mathematically given by,

$$I_F(P) = \frac{1}{W}\sum_{q\in S} G_{\sigma_s}(\| p - q \|)\, G_{\sigma_r}(|I(p) - I(q)|) I(q) \quad (2)$$

where, geometric closeness is $G_{\sigma_s}(\| p - q \|) = e^{-\frac{p-q^2}{2\sigma_s^2}}$

the normalization constant is

$$W = \sum_{q\in S} G_{\sigma_s}(\| p - q \|)\, G_{\sigma_r}(|I(p) - I(q)|) \quad (3)$$

Euclidean distance is $\| p - q \|$ and s is spatial neighborhood of p.

The denoising framework proposed by [10] is a combination of Gaussian Filter and Method noise Thresholding using wavelets (GFMT). The Gaussian filter shows large method noise near the edges and thus the overall method noise which is the difference between corrupted and denoised images is given as, method noise, MN = I - I_F with white Gaussian noise added to the image. This contains image details some edge information, but the estimation of image details and edge details need attention and this is resolved with wavelet domain representation in terms of noisy wavelet coefficient, true wavelet coefficient that is detail coefficient and the Gaussian noise. The detail coefficients are estimated from the noisy wavelet coefficients with a proper thresholding that results in minimum MSE and also retains the original image features.

The threshold for a given subband is expressed as, $T = \frac{\sigma^2}{\sigma_w}$

The median estimator[5] gives the noise variance, σ^2 in the above formula, from subband HH1and σ_w is the variance of wavelet coefficients in that subband. The wavelet transform produces correlated wavelet coefficients, hence, a large wavelet coefficient will probably have large wavelet coefficients at its neighbors. This strategy was applied in image denoising by Chen G Y et.al, [13] and is known as NeighShrink. However, NeighShrink lacks optimal universal threshold and identical window size for subbands. The work done by Chen G Y et.al, [14] presents an adaptive method that estimates an optimal threshold and neighboring window size for NeighShrink in every wavelet subband. NeighShrink strategy is improved using the Stein’s unbiased risk estimate (SURE) by determining an optimal threshold and neighbouring window size for every wavelet subband and is referred to as "NeighShrink SURE" rule.

B. Modelling of proposed method and Methodology

We are proposing a method that applies the threshold to the noisy subband according to NeighShrink SURE rule. The outcome of the analysis given by Zhou and Cheng[15] is given below; unbiased risk on subband s with a window size L is,

$$SURE(w_s,\lambda,L) = N_s + \sum_n \|g_n(w_n)\|_2^2 + 2\sum_n \frac{\partial g_n}{w_n} \quad (4)$$

Threshold and neighboring window sizes are chosen that minimize SURE,

i.e. $(\lambda^s, L^s) = arg_{\lambda,l} minSURE(w_s,\lambda,L)$ (5)

The coefficients are then standardized by using an appropriate estimator. The median of absolute deviation (MAD) [8-12] using highest level of coefficients is the preferred estimator that can be employed.

$$\hat{\sigma} = \frac{\text{median}(|w_s|)}{0.6745} \ (w_s \in \text{subband HH}) \quad (6)$$

The modeling of the proposed method is given as Fig 2.

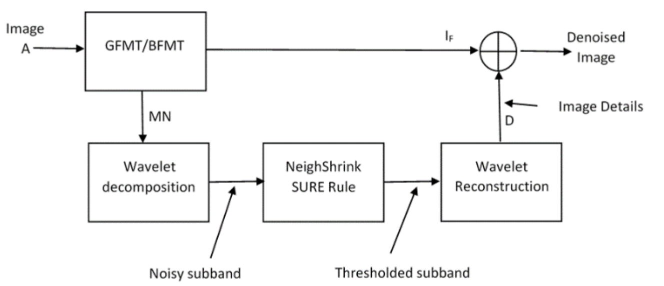

Fig. 2 Proposed Image denoising model

The methodology consists of the following steps;

- Determine the optimal threshold and neighbourhood size
- Compute the risks of all neighbourhood sizes and the corresponding optimal thresholds
- Select the optimal neighbourhood size and the corresponding threshold

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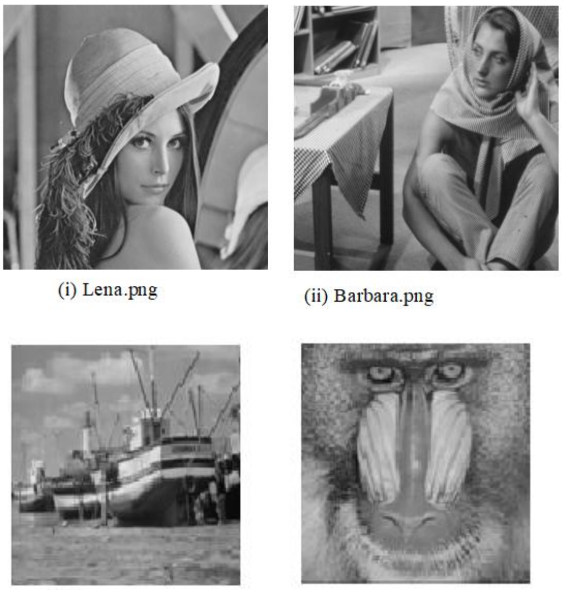
- Threshold the noisy subband using NeighShrink rule
- Output is the thresholded subband

III. RESULTS AND DISCUSSION

We tested our algorithm on four standard gray scale images of dimension 256 x 256. In all the cases the images were added with Gaussian noise with zero mean and standard deviation ranging from 10 to 50. The wavelet used was db8 with the decomposition level of 3 for all the images and for the noise variation from 10 to 50. All the denoised images were tested for the PSNR and IQI parameters with the above specifications. The results were tabulated and the validation of the proposed method was done by comparing the observations with the results obtained by [10] for PSNR and IQI. Our algorithm exhibits an improved performance as compared to Gaussian filter with method noise thresholding (GFMT), Bayesian least square estimate using Gaussian scale mixture (BLSGSM), multiresolution bilateral filter (MRBF) and kernel and wavelet based techniques. It is found that PSNR and IQI parameters obtained from the proposed model show significant improvement over the other methods especially under high noise conditions of σ = 30, 40 and 50.

The standard images used are shown in Fig. 3.



(i) Lena.png (ii) Barbara.png (iii) Boat.png (IV) MANDRILL.PNG

Fig. 3 Standard images of size 256 x 256

The results of the proposed method in comparison with the results tabulated by Shreyamshkumar [10] are summarized in the following tables 1 and 2. The images showing method noise [10] and their respective denoised images for different noise levels are shown in Fig. 4-8 below.

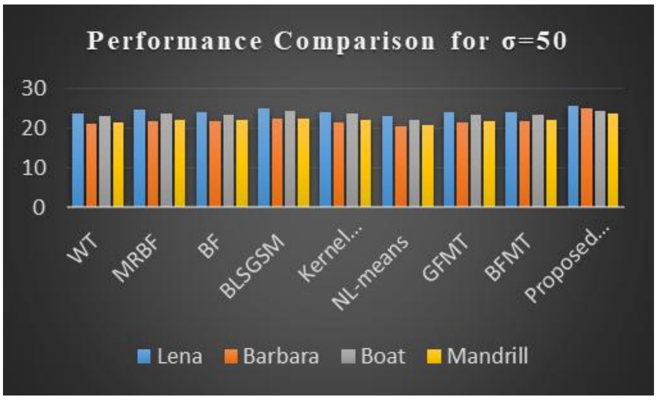


Fig. 4 Performance Comparison for σ = 50

IV. CONCLUSION

In this paper, we have proposed a method that employs the technique of using an optimal threshold and neighbouring window size for every wavelet subband which is key feature of NeighShrink SURE method. The denoising process was applied to the four test images under different noise conditions and results indicate that the proposed method produces on par or even better PSNR results in most of the cases at all noise levels, especially with higher the level of noise. The values for image quality index (IQI) are also significantly better than that of the various methods. Thus the proposed model performs as a better tool for image denoising that improves the image quality for visual perception by retaining the natural details of the image.

TABLE I. COMPARITIVE ANALYSIS IN TERMS OF PEAK SIGNAL TO NOISE RATIO

Noise level, σ	10	20	30	40	50	10	20	30	40	50
Input Image	**Lena 256x256**					**Barbara 256x256**				
WT	30.77	27.31	25.57	24.5	23.7	29.16	24.79	22.7	21.67	21.15
MRBF	31.34	28.24	26.66	25.6	24.67	28.99	24.55	22.91	22.23	21.71
BF	29.28	26.74	25.64	24.85	24.13	24.88	23.17	22.57	22.12	21.69
BLSGSM	33.23	29.8	27.87	26.42	25.18	31.66	27.74	25.63	24.11	22.45
Kernel based	30.13	27.98	26.44	25.22	24.18	24.47	23.6	22.85	22.16	21.51
NL-means	33.6	28.41	25.84	24.16	22.95	30.77	25.81	23.2	21.53	20.44
GFMT	30.85	27.38	25.68	24.6	23.94	29.01	24.67	22.53	21.72	21.39

Proposed method	**34.24**	**30.34**	**28.19**	**26.8**	**25.61**	**32.9**	**29.36**	**27.45**	**26.11**	**25.03**
Input Image	**Boat256x256**					**Mandrill 256x256**				
WT	30.94	27.14	25.23	24.04	23.19	28.45	24.58	23.03	22.18	21.61
MRBF	31.58	27.84	25.89	24.7	23.82	27.64	24.24	23.02	22.44	22.02
BF	28.2	25.67	24.7	24.02	23.41	24.25	23.21	22.77	22.42	22.07
BLSGSM	**32.69**	**28.99**	**27.04**	**25.6**	24.42	30.39	26.2	24.29	23.23	22.5
Kernel based	29.69	27.33	25.75	24.57	23.59	25.85	24.34	23.34	22.65	22.12
NL-means	32.16	27.13	24.41	23.02	22.16	29.32	23.23	21.56	21	20.74
GFMT	31	27.23	25.24	24.04	23.27	28.37	24.49	22.92	22.21	21.77
Proposed method	32.61	28.87	**26.89**	**25.58**	**24.52**	**30.4**	**26.87**	**25.18**	**24.22**	**23.58**

TABLE II. COMPARISON IN TERMS OF IMAGE QUALITY INDEX

Noise level, σ	10	20	30	40	50	10	20	30	40	50
Input Image	**Lena 256x256**					**Barbara 256x256**				
WT	0.988	0.979	0.971	0.963	0.956	0.985	0.964	0.945	0.933	0.927
MRBF	0.991	0.983	0.977	0.972	0.966	0.983	0.962	0.95	0.94	0.936
BF	0.986	0.977	0.972	0.967	0.961	0.964	0.949	0.945	0.939	0.935
BLSGSM	0.994	0.987	0.981	0.976	0.971	0.991	0.980	0.968	0.957	0.942
Kernel based	0.988	0.983	0.979	0.973	0.967	0.961	0.953	0.945	0.939	0.933
NL-means	0.994	0.983	0.974	0.966	0.958	0.989	0.969	0.948	0.927	0.911
GFMT	0.989	0.979	0.971	0.964	0.959	0.984	0.963	0.943	0.934	0.931
Proposed method	**0.994**	**0.987**	**0.98**	**0.973**	**0.966**	**0.992**	**0.938**	**0.978**	**0.973**	**0.967**
Input Image	**Boat256x256**					**Mandrill 256x256**				
WT	0.989	0.974	0.962	0.949	0.939	0.973	0.940	0.917	0.901	0.889
MRBF	0.989	0.980	0.972	0.964	0.956	0.968	0.936	0.918	0.908	0.899
BF	0.983	0.973	0.966	0.956	0.946	0.938	0.923	0.914	0.907	0.899
BLSGSM	**0.993**	**0.984**	**0.977**	**0.969**	**0.963**	**0.982**	0.956	0.936	0.921	0.909
Kernel based	0.987	0.979	0.973	0.966	0.961	0.955	0.936	0.922	0.911	0.901
NL-means	0.988	0.972	0.962	0.952	0.944	0.974	0.923	0.887	0.875	0.871
GFMT	0.989	0.976	0.965	0.951	0.941	0.973	0.939	0.916	0.972	0.891
Proposed method	0.991	0.982	0.971	0.962	0.951	**0.979**	**0.957**	**0.938**	**0.975**	**0.915**

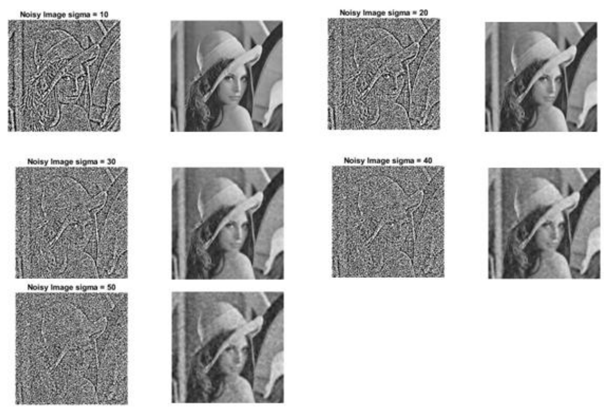


Fig. 5 Noisy and denoised images of Lena.png for σ = 10, 20, 30, 40 and 50

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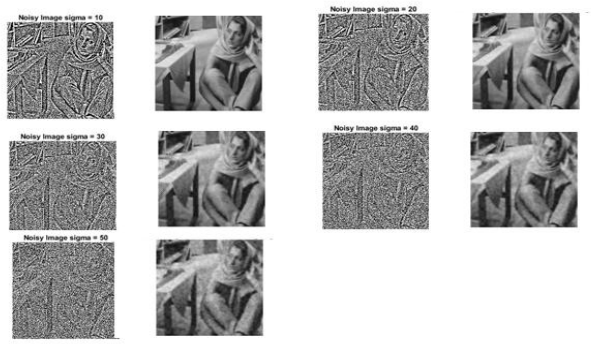
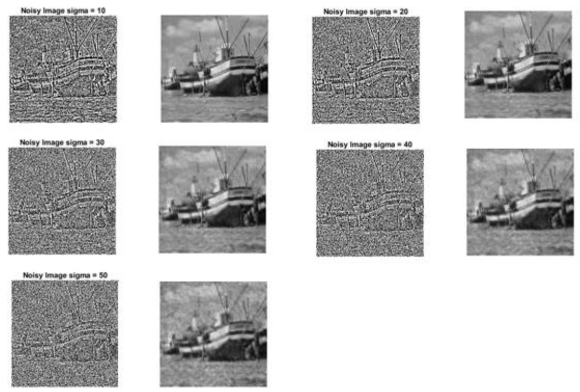


Fig. 6 Noisy and denoised images of Barbara.png for σ = 10, 20, 30, 40 and 50



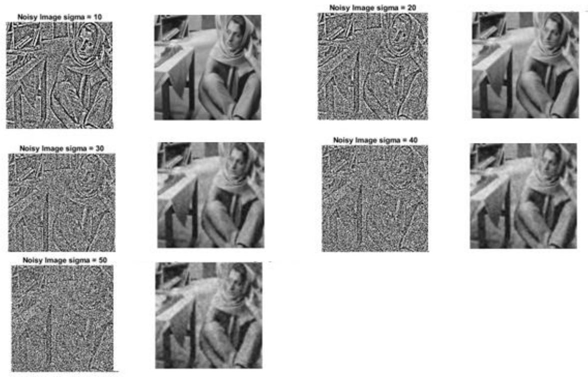


Fig. 7 Noisy and denoised images of Boat.png for σ = 10, 20, 30, 40 and 50

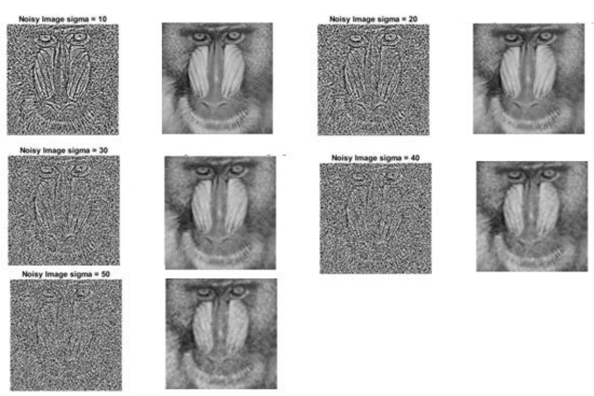


Fig. 8 Noisy and denoised images of Mandrill.png for σ = 10, 20, 30, 40 and 50

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