

An Efficient Image Denoising Method based on Bilateral filter Model and Neighshrink SURE

Mukund N Naragund, Basavaraj N Jagadale, Priya B S, Panchaxri, Vijayalaxmi Hegde



Abstract: In all the instances of image acquisition, transmission and storage, the unwanted noise gets into the information content of the image and thereby introduces an unpleasant visual quality to the observer. So the field of image processing has produced a lot of image denoising algorithms and techniques to improve the visual quality of the image. Since noise cannot be reduced to zero practically, the need for faithful and efficient denoising techniques to produce almost noiseless images demands a systematic research work in the field of denoising methods. The denoising process using a bilateral filter even though produces improvement in the image quality, it does not show consistency when the noise level is high and also the peak signal to noise ratio (PSNR) and Image quality Index (IQI) do not show any improvement. This paper proposes an improved algorithm that incorporates the function of bilateral filter model and wavelet thresholding using Neighshrink SURE method. The results show significant improvement in both PSNR and IQI values with respect to the four standard test images under various noise conditions.

Keywords: Image denoising, Bilateral filter, wavelet thresholding, Neighshrink SURE.

I. INTRODUCTION

At present, the advancement in digital technology, high speed processing and software tools, has resulted in effective image processing that covers a wide range of applications. Image processing domain hence encompasses visible and invisible range of electromagnetic spectrum [1]. Apart from being an advantage it also poses a greater challenge to the researchers to acquire, process and store the image data faithfully without altering the original image content. The noise contaminates the image by disturbing the pixel values, then the denoising method removes, reduces, smoothens or blurs the image to nullify the effect of unwanted pixel

intensities resulted due to noise. The image denoising field has produced a large number of algorithms or methods to reduce the noise and to improve the image quality for the human perception. It is always a crucial decision to select the appropriate denoising technique. It depends on the noise type, as each type needs a suitable denoising method. Way back in 1995, a nonlinear Gaussian filter was proposed by Aurich and Weule [2], but later Tomasi and Manduchi [3] named the filter as bilateral filter. Because of its property of retaining the strong edges of the image, it is widely used in denoising process. It has a simple implementation wherein each picture element is replaced by average of neighboring pixel values and the size and contrast of the image feature are indicated by only two parameters in the mathematical model [4].

The literature [3-6] reports the usage of algorithms using various wavelet families and thresholding techniques, each having its own merit and demerit. In general wavelet denoising has the following steps;

- The noisy image is used as the input for the wavelet transform, in particular discrete wavelet transform
- the test image or noisy image is decomposed into approximation and detail subbands or coefficients
- The approximate subbands with bigger coefficients have image information and wavelet thresholding is applied to the detail coefficients
- As a last step, the approximation and detail subbands are reconstructed into approximate coefficients or subbands but of a lower scale.

Donoho and Johnstone [5-6] proposed two thresholding techniques VisuShrink and SUREShrink operating with universal threshold selection given by eqn. (1),

$$T = \sqrt{2\sigma^2 \log N} \quad (1)$$

Where, σ is noise level, N is length of the corrupted signal. Both thresholding methods use soft shrinkage or thresholding. For VisuShrink, threshold is a function of noise variance and number of samples and for SUREShrink it uses the Stein's unbiased risk estimator (SURE). VisuShrink results in over smoothed image thereby losing some of the image data. SUREShrink performs better than VisuShrink in terms of producing more image details. To overcome drawback of these shrinkage methods, a block thresholding scheme was developed by Cai, Silverman [9], that thresholds the overlapping blocks rather than the individual or term by term. This method depends on the fact that a coefficient has more probability of having signal if neighboring coefficient has one. Later Chen et.al [10,11,13],

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* Correspondence Author

Mukund N Naragund*, Department of Physics and Electronics, CHRIST (Deemed to be University), Bengaluru, India.

Email: mukund.n.naragund@christuniversity.in

Basavaraj N Jagadale, Department of PG studies and research in Electronics, Kuvempu University, Shimoga, India.

Email: basujagadale@gmail.com

Priya B S, Department of Electronics, Kuvempu University, Shimoga, India. Email: preethi2022@gmail.com

Panchaxri, Department of Electronics, SSA Govt. First grade College, Ballari, India. Email: panchakshari21@gmail.com

Vijayalaxmi Hegde, Department of Electronics, MESMM Arts and Science College, Sirsi, India. Email: vijayalaxmih@gmail.com

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applied the concept of neighboring coefficient thresholding for the denoising purpose and called as NeighShrink and showed that this outperforms the other thresholding methods developed earlier by other researchers. Zou and Cheng [14] proposed a method that improved NeighShrink with SURE [12].

This method estimates the optimal threshold and window size in every subband and showed better results for denoising over other methods in terms of Peak signal to noise ratio (PSNR) and Image Quality Index (IQI) parameters.

In this paper, we propose a hybrid scheme for image denoising consisting of a bilateral filter model [15] using Neighshrink SURE rule for wavelet thresholding. The experiment results presented here show the improved denoising effects as compared with other methods [15].

The paper is organized as below;

The section II explains about the related work, a few theoretical concepts defining the work and also discusses the proposed new model for denoising. The section III describes the experiment results and presents the comparison of PSNR and IQI values with the published results. The section IV summarizes the new method, its implementation and finally the conclusion.

II. PROPOSED HYBRID DENOISING MODEL

A. Basic Concepts and related previous work

The Gaussian filter uses a concept of local averaging, that smoothens the image but does not preserve edges. A given pixel will influence the other pixel depending only on the distance and it does not consider the actual value of the pixel. The bilateral filter also produces weighted average of nearby pixels similar to the Gaussian mechanism, but it considers the difference in values with the neighboring pixels while blurring the image to preserve the edges. In other words, for pixel to affect the other, it should have a similar value as well as it should be a neighboring pixel. The mathematical model for the bilateral filter has been discussed by various researchers [2-4] and is usually expressed as (1),

Theoretically,

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q \quad (1)$$

where, BF is the output of the bilateral filter, I is a gray level image for filtering, I_p represents the image value at a pixel position p, W_p is the normalization factor that ensures the weighted sum of pixels to 1.0, and is given by (2), S is the spatial domain, a set of all image locations, \sum symbol denotes a sum over all the pixels indexed by position p, the Euclidean distance is denoted by $\|p - q\|$, σ_s and σ_r spatial parameter and range parameter respectively, represent the amount of filtering for the image I

$$W_p = \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) \quad (2)$$

Where, $G_{\sigma_s}(\|p - q\|) = e^{-\frac{p-q^2}{2\sigma_s^2}}$ is a geometric closeness of the function,

The normalization constant is

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

with Euclidean distance between p and q as $\|p - q\|$ and s being spatial neighborhood of p. As the range parameter increases, the range Gaussian ‘G’ in equation (1) almost remains constant over the intensity interval of the image. Similarly, an increase in spatial parameter, σ_s , smoothens the larger features of the image. The bilateral filter divides an image into two: one, filtered image and another is, its “residual” image. The filtered image holds only the large-scale features, as the bilateral filter removes local variations without affecting the edges. The residual image known as, method noise, is obtained by subtracting the filtered image from the original and it has those image portions that the filter has removed. The work done by [18] introduced a strategy assuming a generalized Gaussian distribution of wavelet coefficients and is called as “BayesShrink” [18]. It has better performance than earlier shrinkage methods in terms of MSE parameter. The combination of Gaussian and bilateral filters with BayesShrink thresholding yielded a better results in terms of PSNR and Image quality index (IQI) in comparison with various methods as demonstrated by [15].

As bilateral filter with method noise thresholding (BFMT) model. This model thresholds the method noise wavelet coefficients. The optimal threshold and length of the signal must be data driven and also must minimize the mean squared error (MSE). This is not achieved by the BayesShrink strategy, but Stein’s unbiased risk estimate (SURE) states that MSE estimation is possible unbiasedly from the data obtained. With this estimate, [14] improved NeighShrink with SURE. They have determined an optimal threshold and neighborhood window size for every subband or coefficient using SURE. Although there has been a lot of work on usage of Gaussian filters in combination with BayesShrink strategy [15] but all results have not produced significant denoising with edge preservation. A hybrid model [20] of Gaussian filter with NeighShrink SURE was proposed to show improvement in image quality. In this paper an improved denoising method using bilateral filter is presented.

B. Improved method with NeighShrink SURE rule

Since the BFMT model proposed by [15], uses the BayesShrink thresholding, which lacks consistency in performance with regard to noise levels, we have developed an improved denoising method that incorporates the benefits of NeighShrink SURE algorithm [14] along with bilateral filter model. The proposed method is represented by the following block diagram in Fig. 1.

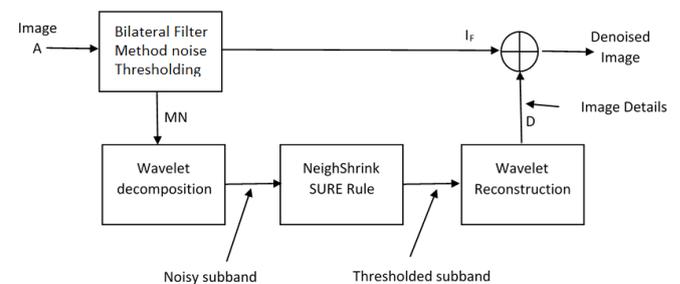


Fig. 1 Block diagram of the proposed denoising method

According to the mathematical analysis stated by [14], Unbiased risk on subband s with a window size L is,

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

Threshold and neighboring window sizes are chosen that minimize SURE,

$$i.e. (\lambda^s, L^s) = arg_{\lambda, L} min SURE(w_s, \lambda, L) \quad (5)$$

The coefficients are then standardized by using an appropriate estimator. The median of absolute deviation (MAD) [2-3] using highest level of coefficients is the preferred estimator that can be employed and is given by

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

In the proposed method, A is original image and I_F is the output of the filter operator, the residual image, called, "method noise"[15], is the difference between noisy image and denoised image as given by, $MN = A - I_F$. The method noise consists of noise as well as image details and image details, since bilateral filter is used, the edges are preserved by range filtering. Wavelet thresholding removes noise components in detail subbands of method noise. Now we apply Neighshrink SURE rule for the subband thresholding. The methodology is represented by the flowchart shown in Fig.2;

Db8 is used as the wavelet decomposition with decomposition level of 3 and NeighShrink SURE is used the threshold these subbands or coefficients. The study was performed for Peak signal to Noise Ratio (PSNR) and Image Quality Index (IQI). To prove the validity of our proposed algorithm, we compared these results with results obtained by denoising methods available in literatures like, wavelet transform (WT), Multiresolution bilateral filter (MRBF), Bayesian least squares estimate using Gaussian scale mixture (BLS-GSM) and Bilateral filter and its method noise thresholding (BFMT). Our method shows an improved performance as compared to BFMT, MRBF, WT for all test images and noise levels. The resulting images are shown in Fig. 6-9. The results tabulated below show a significant enhancement in the denoised image in terms of visual quality index and PSNR especially with noise levels, 30, 40 and 50. The results achieved for Lena and Barbara images at higher noise levels outperforms all the other denoising methods listed by [15]. Similarly the IQI values for all the images except Boat image exhibit enhanced performance with our method. The line charts drawn for the PSNR variations obtained for Lean and Barbara images gives a comparison with BFMT and BLSGSM methods.

Table I Comparison of proposed method with other denoising methods for PSNR values

| σ | 10 | 20 | 30 | 40 | 50 | 10 | 20 | 30 | 40 | 50 |
|------------------------|---------------------|--------------|--------------|--------------|--------------|------------------------|--------------|--------------|--------------|--------------|
| | 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 |
| BLSGSM | 33.23 | 29.8 | 27.87 | 26.42 | 25.18 | 31.66 | 27.74 | 25.63 | 24.11 | 22.45 |
| BFMT | 31.63 | 27.95 | 26.11 | 24.97 | 24.18 | 29.16 | 24.87 | 22.91 | 22.16 | 21.72 |
| Proposed method | 34.24 | 30.34 | 28.19 | 26.8 | 25.61 | 32.9 | 29.36 | 27.45 | 26.11 | 25.03 |
| | Boat 256x256 | | | | | Baboon 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 |
| BLSGSM | 32.69 | 28.99 | 27.04 | 25.6 | 24.42 | 30.39 | 26.2 | 24.29 | 23.23 | 22.5 |
| BFMT | 31.48 | 27.55 | 25.51 | 24.32 | 23.49 | 28.58 | 24.83 | 23.25 | 22.49 | 22.01 |
| Proposed method | 32.61 | 28.87 | 26.89 | 25.58 | 24.52 | 30.4 | 26.87 | 25.18 | 24.22 | 23.58 |

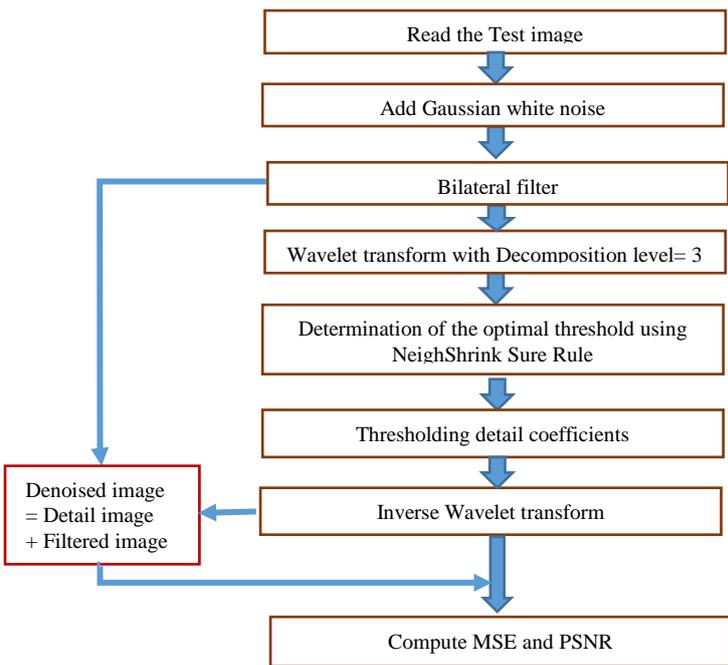


Fig. 2 Flowchart for the denoising method

III. EXPERIMENTAL RESULTS AND DISCUSSION

Fig.5 shows the four standard images of dimension 256 x 256 used as the test images in our method. The images were corrupted with the Gaussian noise with zero mean and noise variance (σ^2) with values 10, 20, 30, 40 and 50.

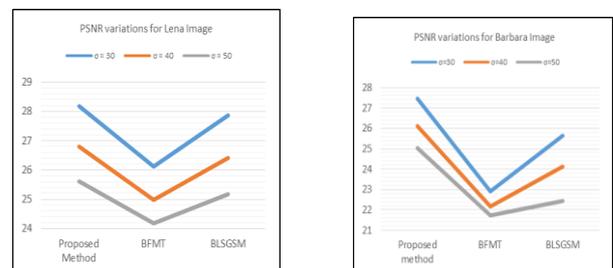


Fig. 3 Comparison of PSNR Variations for Lena and Barbara images

Table II Comparison of proposed method with other denoising methods for IQI values

| σ | 10 | 20 | 30 | 40 | 50 | 10 | 20 | 30 | 40 | 50 |
|------------------------|---------------------|---------------|---------------|---------------|---------------|------------------------|---------------|---------------|---------------|---------------|
| | Lena 256x256 | | | | | Barbara 256x256 | | | | |
| WT | 0.9888 | 0.9799 | 0.9711 | 0.9634 | 0.9567 | 0.9846 | 0.9637 | 0.9449 | 0.9331 | 0.9272 |
| MRBF | 0.9905 | 0.9827 | 0.9768 | 0.9721 | 0.9664 | 0.9834 | 0.962 | 0.9467 | 0.9398 | 0.9356 |
| BLSGSM | 0.9939 | 0.9872 | 0.9813 | 0.976 | 0.971 | 0.9914 | 0.9802 | 0.968 | 0.9572 | 0.9422 |
| BFMT | 0.9905 | 0.9808 | 0.9729 | 0.965 | 0.9589 | 0.9841 | 0.9644 | 0.9473 | 0.9389 | 0.9349 |
| Proposed method | 0.9943 | 0.9874 | 0.98 | 0.973 | 0.9662 | 0.9919 | 0.938 | 0.978 | 0.973 | 0.9672 |
| | Boat256x256 | | | | | Baboon 256x256 | | | | |
| WT | 0.9889 | 0.9746 | 0.9624 | 0.9486 | 0.9398 | 0.973 | 0.9403 | 0.9171 | 0.9011 | 0.8885 |
| MRBF | 0.9898 | 0.9803 | 0.9727 | 0.9644 | 0.9562 | 0.9687 | 0.9363 | 0.9183 | 0.9076 | 0.8989 |
| BLSGSM | 0.9931 | 0.984 | 0.9768 | 0.9694 | 0.9634 | 0.982 | 0.9561 | 0.9357 | 0.9211 | 0.9097 |
| BFMT | 0.9903 | 0.978 | 0.9668 | 0.9533 | 0.9424 | 0.9735 | 0.9429 | 0.9219 | 0.9074 | 0.897 |
| Proposed method | 0.9914 | 0.982 | 0.9714 | 0.9616 | 0.9513 | 0.9798 | 0.9568 | 0.9381 | 0.9249 | 0.9149 |

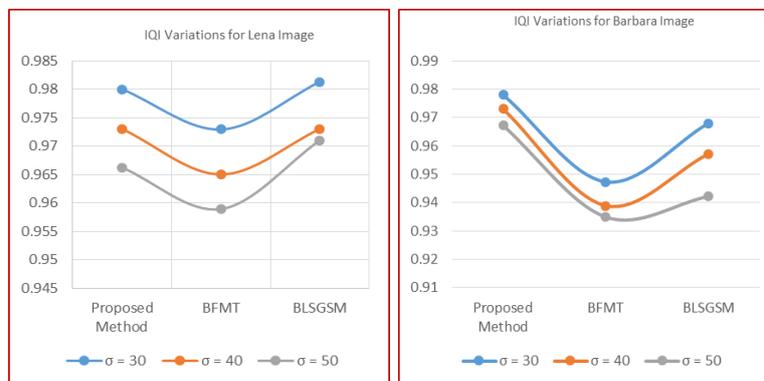


Fig. 4 Comparison of IQI Variations for Lena and Barbara images

IV. CONCLUSION

In this paper we improved the performance of bilateral filter model (BFMT) by using Neighshrink thresholding with Stein's unbiased risk estimate (SURE). This determines the optimal threshold and the window size for each subband in the neighborhood. The above said denoising technique is applied to the four standard images Lena, Barbara, Boat and mandrill with 256x256 size and PNG (Portable Network Graphic) formats. We tested the method for different values of noise standard deviation, $\sigma = 10, 20, 30, 40$ and 50 and tabulated the results for the comparative study of various denoising methods. The comparison shows that our improved denoising model produces on par or even better PSNR values, at all noise levels as compared with the other established denoising methods. The results corresponding to the IQI values also show a significant enhancement for visual quality in comparison with BFMT and other methods. Hence, the proposed model proves to be efficient denoising method that results in better PSNR and IQI, thereby improving the

overall image quality with edge preservation for the visual perception for the user.



Fig. 5. Standard Test Images Lena.png, Barbara.png, Boat.png and Mandrill.png of 256x256 size



Fig. 6 Denoised images of Lena.png for noise level 10,20,30,40 and 50



Fig. 7 Denoised images of Barbara.png for noise level 10,20,30,40 and 50



Fig. 8 Denoised images of Boat.png for noise level 10,20,30,40 and 50



Fig. 9 Denoised images of Mandrill.png for noise level 10,20,30,40 and 50

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An Efficient Image Denoising Method based on Bilateral filter Model and Neighshrink SURE

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has published more than 30 articles in research journals and also worked as reviewer for journals.



Priya B S has done her post-graduation in Electronics from Kuvempu University and currently she is a research scholar pursuing her PhD in the Department of PG studies and research in Electronics, Kuvempu University, Shimoga, India. Her research area is Image processing and in particular Image analysis for quantification.



Panchaxri has completed MSc in Electronics from karnatak University, Dharwad and presently he is working as an Assistant Professor in the Department of Electronics, SSA Govt First Grade College, Ballari, India. He is having teaching experience of about 12 years. His teaching interests are Electronic communication, microcontrollers. His research field is DSP and Image processing.



Vijayalaxmi Hegde has completed her MSc in Electronics from Karnatak University, Dharwad and MTech from Karnataka State Open University, Mysuru, India. She is working in the Department of Electronics, MESMM Arts and Science College, Sirsi, India, as an Assistant Professor. Her research interests are wireless sensor networks and Image processing.

AUTHORS PROFILE



Mukund N Naragund has completed his MSc (Electronics) from Karnataka University, Dharwad, India and MPhil from Bharathidasan University, Trichy, India. He is an Associate Professor in the Dept. of Physics and Electronics, CHRIST (Deemed to be University), Bengaluru, India. He is also a research scholar in Department of PG studies and

research in Electronics, Kuvempu University, Shimoga, India. His teaching interests are Digital logic design, Verilog, FPGA, Embedded systems and Electronic Instrumentation. His area of research is digital signal and Image processing



Dr. Basavaraj N Jagadale He is working as Assistant Professor in the Department of PG studies and research in Electronics, Kuvempu University, Shimoga, India. He has done his PhD, from Karnataka University, Dharwad, India. He has worked in Radiology Dept., University of Pennsylvania, USA under UGC Raman fellowship

sponsored by the govt. of India, for the Post-doctoral research during 2015-16. His research interest is signal and image processing domain and