

An Efficient Image Denoising Based on Wiener Filter and NeighSure Shrink



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

Abstract: Wiener filter denoise the image using linear stochastic framework. It eliminates the noise by estimating optimal filter for noisy input image by minimizing the mean square error between the desired image and estimated image. The main drawback of this filter is the performance is reduced when the noise is random and unknown as it has fixed frequency response for all frequencies. The efficiency of this filter can be increased by incorporating method noise thresholding using NeighSure shrink. This paper presents a method which is a blend of Wiener filter and wavelet based NeighSure shrink thresholding. The results indicates that the proposed method is significantly superior than wavelet thresholding, Wiener filter and Gaussian filter with its method noise thresholding techniques in terms of visual quality, Peak Signal to noise ratio and image quality index.

Keywords : Discrete Wavelet Transform, NeighSure shrink, Wavelet thresholding, Wiener filter

I. INTRODUCTION

Images are contaminated by noise during acquisition and transformation [1]. These images should be denoised before using them in image processing applications. Image denoising is the method of eliminating noise from the image, while conserving important image features. From past few decades researchers have developed different image denoising techniques to remove noise from an image and still it is a challenging task for a researcher.

Images are denoised in mainly two domains, spatial domain and transformed domain. In spatial domain, images are denoised directly by employing intensity values of the pixel. In transformed domain, images are transformed to frequency domain and the coefficients are used to denoise the image.

Median filtering [2] is a spatial nonlinear filter employed to eliminate impulsive or salt-and-pepper noise.

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* Correspondence Author

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

Basavaraj N Jagadale, Department of PG studies and research in Electronics, Kuvempu University, Shimoga, India. Email: basujagadale@gmail.com

Mukund N Naragund, Department of Physics and Electronics, CHRIST(Deemed to be University, Bengaluru, India Email: mukund.n.naragund@christuniversity.in

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

Panchaxri, Department of Electronics, SSA Govt. First grade College, Ballari, India. Email: panchaksharih21@gmail.com

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This filter substitutes the pixel under consideration with the median value of the neighboring window. It reduces the noise while preserving edges. Gaussian filters [3] are designed denoise additive Gaussian noise. Mathematically, a Gaussian filter convolves the input signal with a Gaussian function to denoise an image. The Gaussian filter is usually used as a smoother. Inverse filters are linear filters [4] used to remove the image blurring when it is blurred by a known low pass filter. But this filter is sensitive to noise. The Wiener filtering [5] is a linear stochastic approximation of the original image which de-blur the image along with the denoising. But this filter removes some edges.

Donoho et [6] all proposes an image denoising technique in wavelet transfer (WT) domain, which decomposes the image into lower frequency and higher frequency coefficients. Lower frequency coefficients are also known approximation coefficients and higher frequency coefficients are called detailed coefficients. The approximation coefficients contain low frequency signal and do not contain noise, whereas the detailed coefficients are higher frequency signals in which noise is distributed uniformly. Image denoising can be done by thresholding the higher frequency coefficients. Steps to denoised an image using wavelet transform is summarized as follows,

1. Decompose the image using discrete wavelet transform (DWT) into approximation and detailed coefficients.
2. Apply thresholding on the higher frequency coefficients.
3. Perform inverse discrete wavelet transform to obtain the denoised image.

The wavelet coefficients are commonly thresholded [7] by either hard thresholding or soft thresholding. In both techniques the coefficients lesser than the threshold value were reduced to zero. The coefficients larger than threshold were kept unchanged in hard thresholding whereas, soft thresholding, shrinks the larger coefficients to zero by a threshold value. The selection of a threshold is an important criterion in wavelet denoising technique. Smaller threshold value may leave some noise in the denoised image and the larger threshold value may remove some image features. Therefore, threshold value should be optimal, so that noise is removed while preserving image information.

This paper presents a hybrid image denoising scheme amalgamation of a Wiener filter and wavelet thresholding using NeighSure Shrink. The experimental results demonstrate better results in terms of Peak Signal to Noise Ratio (PSNR) and Image Quality Index (IQI).

The paper is planned as follows: Section II gives an ephemeral review of the different wavelet thresholding techniques, Section III introduces some basics of Wiener filter, the proposed method is presented in section IV, section V discuss results, including comparison with other denoising techniques and conclusions, are summarized in section VI.

II. WAVELET THRESHOLDING TECHNIQUES

A. Vishu Shrink

Donoho proposes [8] a universal thresholding technique called VisuShrink thresholding. This technique uses the same threshold value for all detailed subbands. The threshold value T is in proportional with standard deviation of noise and it is calculated using,

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

where, σ is the estimated noise deviation and N represents the total number of pixels in the image. As this thresholding depends on the number of pixels N , it produces over smoothed images.

B. Sure Shrink

Choosing a common threshold value for all subbands reduces the performance of Visu shrink. In Sure shrink [9] a distinct threshold value is estimated for every subband using Stein's unbiased risk estimator (SURE). It selects an optimal threshold value for every subband which reduces Stein's unbiased risk estimator, given by

$$\lambda_s = \arg \min_{t \geq 0} SURE(t, L, D_s) \quad (2)$$

where, $SURE(t, L, D_s) = N_s - 2 \sum_{x,y=1}^{N_s} \left[\min(|D_{xy}|, t) \right]^2$ and D_s represents the wavelet coefficients of subband S and N_s is the total number of coefficients in corresponding subband D_s .

C. Bayes Shrink

SureShrink perform well when coefficients are not very sparse and it is upgraded by Chipman [10] by replacing stein's unbiased risk factor by Bayes mathematical frame work to estimate the threshold value and computed the threshold value that reduces the Bayesian risk in each detail subband.

$$\lambda_B = \frac{\hat{\sigma}^2_{noise}}{\hat{\sigma}_{noise}} = \frac{\hat{\sigma}^2_{noise}}{\sqrt{\max \left(\hat{\sigma}_G^2 - \hat{\sigma}^2_{noise}, 0 \right)}} \quad (3)$$

where $\hat{\sigma}_G^2 = \frac{1}{N_s \sum_{x,y=1}^{N_s} G_{xy}^2}$ and N_s is the number of

wavelet coefficients G_{xy} on the subband under consideration.

D. NeighSure Shrink

Z. Dengwen et. Al. [11] propose an improved version of Sure shrink called Neigh shrink sure. In this method, Stein's Unbiased Risk Estimator is employed to calculate the best threshold value and neighboring window size. The noisy detailed coefficients are arranged into the 1-dimensional

vector $W_s = \{W_n; n=1, 2, \dots, N_s\}$. Likewise, 1-dimensional unknown noiseless co-efficients $\theta_s = \{\theta_n; n=1, \dots, N_s\}$ are combined. The expected loss $E\{\|\hat{\theta}_s - \theta_s\|_2^2\}$ can be estimated unbiasedly using SURE.

$$E\{\|\hat{\theta}_s - \theta_s\|_2^2\} = E\{SURE(t, L, G_s)\} \quad (4)$$

First, $SURE(t, L, G_s)$ is estimated and then best threshold t_s and neighboring window size L_s for a subband s which reduces $SURE(t, L, G_s)$ is selected using (5)

$$(t_s, L_s) = \arg_{\lambda, L} SURE(G_s, t, L) \quad (5)$$

where, t_s and L_s are calculated by assuming the $\sigma=1$. When noise variance is not equal to one, then For σ is estimated using following equation,

$$\hat{\sigma} = \frac{\text{median}(|W_s|)}{0.6745} (W_s \in \text{subbandHH}) \quad (6)$$

III. WEINER FILTER (WF)

The Wiener filter [5] [12] is a stationary linear filter that optimizes Mean Square Error (MSE). It assumes both the signal and noise are stationary and uncorrelated. This filter removes the noise in the signal by estimating noiseless signal which minimizes MSE. It uses both degradation function and statistical characteristics of the noise to denoise the image. The Wiener filter is given by,

$$W(x, y) = \frac{H^*(x, y)}{|H(x, y)|^2 + \frac{1}{SNR}} \quad (7)$$

where, $H(x,y)$ represents the degradation function, $H^*(x,y)$ is the complex conjugate of degradation function, SNR is the Signal to Noise Ratio.

IV. PROPOSED METHOD

B.K Shreyamsha Kumar proposes the GFMT [13] filter that uses both Gaussian filter and wavelet thresholding based on BayesShrink [10]. The objective of BayesShrink is to reduce the Bayesian risk formula. This method produces vanished features like homogeneous area, important features like edges and textures are vanished [14]. The proposed technique improves GFMT filter by replacing Gaussian filter by Wiener filter and BayesShrink by NeighSure shrink.

The proposed method is amalgamation of Wiener filter (WF) and Wavelet thresholding (WT) techniques. It uses the advantages of both WF and WT to denoise the image. The noisy image (IN) is first filtered by Wiener filter, and then method noise image is obtained by taking the difference of the noisy image and image filtered by Wiener filter. Wiener filter remove the noise present in the image but it removes some edges in the image. Method noise (MN) image consists of the edges and image information removed by Wiener filter. These edges and information are preserved using wavelet thresholding using NeighSure shrink.

Method Noise is one of the performance measuring criterions of the denoised technique.

If the MN of the any denoised method contains any image information and edges then it is a poor denoising technique, if it looks like a noise without any image information then it is a best denoising technique. Here, in this proposed denoising technique, we denoise MN of the Weiner filter by using NeighSure shrink, and then the resultant image is added to image denoised by Weiner filter.

Algorithm: To denoise an image using the proposed method:

Input: Noisy Image

Output: Denoised image

Step 1: Apply Weiner filter on the noisy image to obtain I_F .

Step 2: Obtain Method noise (MN) by taking the difference of the noisy image and the image denoised by Weiner filter

Step 3: Perform wavelet transform on the MN image and decompose the image into 3 level approximation and detailed coefficients.

Step 4: Threshold detailed coefficients using NeighSure shrink.

Step 5: Apply inverse Wavelet transform and obtain D_{WT}

Step 6: Add D_{WT} and I_F to get denoised image.

V. RESULTS AND DISCUSSION

A. Experimental setup

The proposed method is executed in MATLAB and compared with WT, WF, GFMT methods by choosing various 256X256 gray scale images shown in fig.1. Images are corrupted by additive Gaussian noise of standard deviation 10,20,30,40,50. Standard images Lena, Barbara and boat are denoised with WT, WF, GFMT and proposed methods. The effectiveness of the proposed methods is compared with WT, WF, GFMT methods in terms of PSNR and IQI. In this experiment image is decomposed into three levels using db8 wavelet.



Fig 1: a) lena.png b) barbara.png c) boat.png

B. Performance matrices

Peak Signal to Noise Ratio (PSNR)

PSNR reflects the relationship between denoised image and original image. A higher PSNR means better quality of the denoised image. It is defined as,

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE} \quad (8)$$

where, MAX represents maximum intensity of the denoised image and MSE is the Mean Squared Error of the original image and denoised image.

Image Quality Index

IQI is calculated by taking the product of luminance distortion, loss of correlation and contrast distortion of the image. The range of IQI is [-1, 1], IQI of 1 means original image is equal to denoised image.

C. Comparison



Fig (2): a)Noisy image with $\sigma=20$, image denoised by b)WT c)WF d)GFMT e)Proposed method

Table-I: Comparison of PSNR scores of the denoised images

σ	10	20	30	40	50
Method used	Input Image : LENA				
WT	30.77	27.31	25.57	24.50	23.70
WF	30.08	28.36	26.60	25.12	23.86
GFMT	30.85	27.38	25.68	24.6	23.94
Proposed method	33.10	28.95	26.80	25.22	23.95
	Input Image: Barbara				
WT	29.16	24.79	22.7	21.67	21.15
WF	28.95	27.29	25.80	24.48	23.30
GFMT	29.01	24.67	22.53	21.72	21.39
Proposed method	31.83	28.15	26.12	24.73	23.53
	Input Image: Boat				
WT	30.94	27.14	25.23	24.04	23.19
WF	28.32	26.73	25.26	23.96	22.86
GFMT	31.00	27.23	25.24	24.04	23.27
Proposed method	31.60	27.65	25.62	24.14	23.38

Table II: Comparison of IQI of the denoised images

σ	10	20	30	40	50
Method used	Input Image : LENA				
WT	0.9888	0.9799	0.9711	0.9634	0.9567
WF	0.9890	0.9825	0.9743	0.9643	0.9529
GFMT	0.9891	0.9797	0.9713	0.9639	0.9586
Proposed method	0.9931	0.9839	0.9747	0.9648	0.9534
	Input Image: Barbara				
WT	0.9846	0.9637	0.9449	0.9331	0.9272
WF	0.9840	0.9777	0.9697	0.9609	0.9520
GFMT	0.9839	0.9632	0.9429	0.9341	0.9310
Proposed method	0.9910	0.9820	0.9730	0.9623	0.9521
	Input Image: Boat				
WT	0.9889	0.9746	0.9624	0.9486	0.9398
WF	0.9791	0.9733	0.9647	0.9523	0.9388
GFMT	0.9892	0.9762	0.9653	0.9514	0.9411
Proposed method	0.9896	0.9760	0.9657	0.9579	0.9449



Fig (3): Barbara image denoised by proposed with standard deviation a) 10 b) 20 c) 30 d) 40 e) 50

To evaluate the efficiency of the proposed denoising method, it is compared with WT, WF, and GFMT methods. Table-I and Table-II compares the PSNR and IQI values of the proposed method with WT, WF and GFMT methods. It is detected from the experiment that the image denoised by proposed method has highest PSNR than other methods. When noise SNR is low, proposed method performs well but

when noise SNR is high, the performance of the proposed method is comparable.

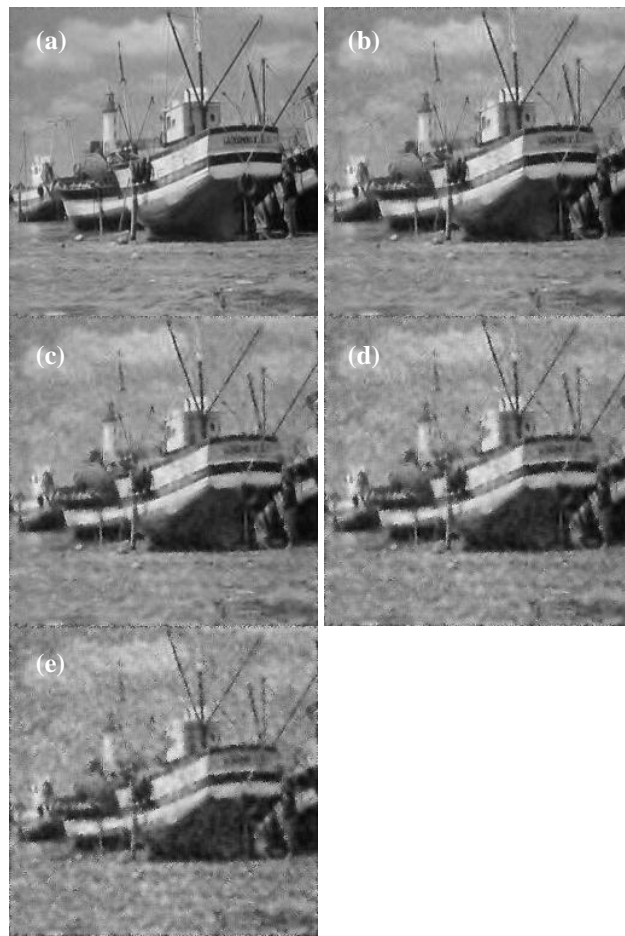


Fig (4): Boat image denoised by proposed with standard deviation a) 10 b) 20 c) 30 d) 40 e) 50

Fig.2(a) shows the lena image corrupted by Gaussian noise with $\sigma=20$, from Fig.2b, 2c, 2d, and 2e it can be seen that WT, WF smooth the images, GFMT produces artifacts and the images denoised by proposed method are better in visual quality than other methods under comparison and also it preserve edges. Fig (3) and (4) displays images denoised by proposed method with standard deviation 10, 20, 30, 40, 50.

VI. CONCLUSION

This paper attempts to improve GFMT method proposed by B.K Shreyamsha Kumar. The proposed method uses optimal NeighSure shrink which preserves the edges and image information removed by Wiener filter. The experimental outcomes suggest that the proposed method outperforms WT, WF and GFMT denoising techniques and visual quality of the image denoised by proposed method is better than other methods under consideration.

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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.



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



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.



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