An Adaptive Image Denoising Method based on Thresholding

HARI OM AND MANTOSH BISWAS
Department of Computer Science & Engineering
Indian School of Mines, Dhanbad
Jharkand-826004
INDIA
{hariom4india, mantoshb}@gmail.com

Abstract - This paper proposes an Adaptive Image Denoising Method based on Thresholding that follows the similar approach as in the NeighShrink method. This method shrinks the noisy wavelet coefficients using an adaptive threshold. The NeighShrink and its versions namely, IAWDMBNC and IIDMWT always produce unfavourable smoothing of edges and details of the noisy image because these methods kill more noisy coefficients during the shrinkage. Our proposed method overcomes these drawbacks and performs better than the NeighShrink, IAWDMBNC, and IIDMWT in terms of Peak Signal-to-Noise Ratio (PSNR) using shrinkage based on our proposed threshold.

Key-Words - Image Denoising, Thresholding method, Coefficient, Peak Signal-to-Noise Ratio (PSNR).

1 Introduction

The noise removal from a noisy image is a problem that exists from the very beginning of the digital image processing. This problem still attracts research attention and wide ranges of various approaches have been discussed to remove the noise and preserve the image information. The aim of noise removal is to construct the original image from the noisy observation. In recent years, the wavelets transform (WT) based approaches have led to a substantial success in image denoising due to good localization in both the spatial and spectral domains [1-2]. The image denoising methods may be based on term-by-term or block-by-block thresholding [3-11]. Donoho et al. discuss the term-by-term thresholding such as VisuShrink, SureShrink and the block-by-block thresholding such as NeighBlock, NeighShrink, IAWDMBNC, and IIDMWT have been discussed by Cai et al., Bui et al., Jun Jiang et al., and Om et al., respectively. The block-by-block thresholding methods are based on subband adaptive neighboring window and have better performance than the term-by-term based methods. The VisuShrink [3-4] method offers the advantages of smoothness and adaptation; however, it exhibits visual artifacts due to Gibbs phenomena in the neighbourhood of discontinuities. Overcoming this problem, Coifman and Donoho have discussed SureShrink. It is based on Stein's Unbiased Risk Estimator (SURE) that minimizes the mean squared error [5]. The NeighBlock method discussed takes the neighbouring coefficients into account [6]. Chen and Bui have extended the neighboring wavelet thresholding idea, called NeighShrink, for multiwavelet that outperforms the single wavelet denoising method for the standard test signals and real-life images [7-8]. Jun Jiang et al. and Om et al. have improved the NeighBlock and NeighShrink methods [9-10]. Our proposed method is also based on Jun Jiang et al.s' method, which takes into account the local characteristics of the neighboring window, size of the subband, and the noise distribution at different decomposition levels of the noisy image. The effectiveness of our method over the NeighShrink, IAWDMBNC, and IIDMWT is due to the noise removal, which is also shown in experimental results in terms of peak-to-signal ratio (PSNR). The organization of rest of the paper is as follows. Section 2 describes the proposed method in detail. Section 3 discusses the experimental results carried out, and finally the paper is concluded in Section 4.

2 Proposed Method

Let a noise-free image X be corrupted by independent and independent identically distributed (i.i.d.) additive white Gaussian noise N that has zero-valued mean and variance as σ^2. The corresponding noisy image is denoted by Y. Mathematically, we can write

$$Y_{m,n} = X_{m,n} + N_{m,n} \qquad (1)$$

Here, $1 \leq m, n \leq M$; M×M is original image size.

The main goal of our method is to minimize the mean square error (MSE) of the noisy image $Y_{m,n}$ and original image $X_{m,n}$. Let $W(\cdot)$ and $W^{-1}(\cdot)$ denote the forward and backward wavelet transform operators and $D(\cdot, T)$ denote the denoising operator with threshold T [2]. We denoise Y to recover $\hat{X}$ as an estimate of the original image X after applying the following three steps:

(i) Forward operator to noisy image Y i.e. Z = W(Y).
(ii) Denoising operator to Z i.e. O = D (Z, T).
(iii) Inverse wavelet transform to reconstruct the image $\hat{X}$ from O i.e., $\hat{X} = W^{-1}(O)$.

For carrying out above steps, we need to derive threshold using which the shrinkage factor is evaluated and finally the denoising procedure is applied.

2.1 Parameter Estimation

Let $Sq^2_{m,n}$ be a summation square of the wavelet coefficients by incorporating neighbouring coefficients in thresholding process. In other words, we have

$$Sq^2_{m,n} = \sum_{(p,q)\in B_{m,n}} d^2_{p,q} \qquad (2)$$

where, $B_{m,n}$ represents the neighborhood window whose elements are denoted by $d_{p,q}$. For every wavelet coefficient, we consider a square neighborhood window $B_{m,n}$ of size L×L centered at that pixel, where L is a positive odd integer.

We take several useful values of neighboring coefficients that are needed for choosing an appropriate threshold. Let $Sq_{\max}$ and $Sq_{\min}$ represent maximum and minimum summation square, respectively, of $Sq^2_{m,n}$ at the same decomposition level as defined below [9]:

$$Sq_{\max} = \max(Sq^2_{m,n}), \text{ and}$$

$$Sq_{\min} = \min(Sq^2_{m,n}) \qquad (3)$$

2.2 Threshold Estimation

The NeighShrink denoising method uses the VisuShrink threshold that produces the over-smoothed signal since its threshold is large [7-8]. This problem has been overcome in IAWDMBNC and IIDMWT by using their shrinkages followed by the modified threshold of the VisuShrink threshold with maximum and minimum sums of the wavelet coefficients window at the same level [9-10]. However, theses methods are not able to remove the noise and restore the modified noisy coefficients efficiently since they kill many noisy coefficients because of their large thresholds. In this proposed work, we try to overcome this problem by using the shrinkage followed by our proposed threshold function. Here, we change the VisuShrink threshold and other parameters of the noisy image in such a way that the threshold value is neither large nor less of the noisy coefficients. Hence, this proposed method removes the noise effectively as the small threshold keeps more features of the signal, whereas large threshold eliminates the noise as much as possible. Therefore, we need to define our threshold as follows.

$$T^{NEW}_{m,n} = \frac{Sq_{\max} - Sq_{m,n}}{Sq_{\max} + Sq_{\min}} * t \qquad (4)$$

where, the scale factor, t, is given by [10]

$$t = \sigma \sqrt{\log \frac{\hat{M}}{l}} \qquad (5)$$

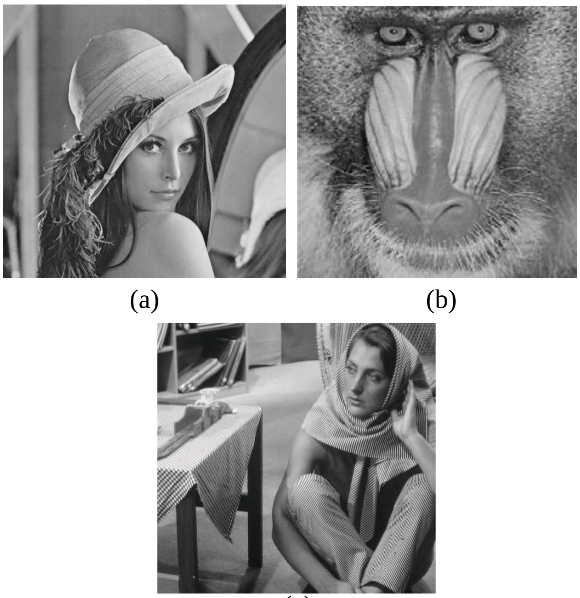
Here, $l = 1, 2, \ldots, J$; J denotes the decomposition level to be considered and $\hat{M} = M/2^l$.

2.3 Shrinkage Estimation

After estimating the threshold $T^{NEW}_{m,n}$, we need shrink the wavelet coefficients using the following formula.

$$\bar{X}_{m,n} = Z_{m,n}\left(1 - \left(\frac{T^{New}_{m,n}}{Sq_{m,n}}\right)^l\right)_+ \qquad (6)$$

The shrinking operation counterbalances the deficiency of soft thresholding that can keep more information of the signal. The degree of shrinkage in our thresholding decreases as the decomposition level l increases. The shrinkage factor correlates the wavelet coefficients and decomposition levels (i.e. l) and '+' sign at end of the expression signifies that the positive value should be kept and the negative value should be set as zero.



(a) (b)

(c)

Fig. 1: Original test gray images: (a) Lena (b) Mandrill and (c) Barbara each of size 512×512 pixels

2.3 Denoising Procedure

The following steps are performed in the denoising scheme:

(i) Perform multiscale decomposition on the corrupted image. For this, apply 2-D wavelet transform W on the noisy image Y up to J^{th} level to generate several subbands: HH, HL, and LH, called details, and LL, called approximation.

(ii) For each level, compute $T_{m,n}^{NEW}$ using (4).

(iii) For each subband (except the low pass residual, i.e. approximation), shrink the wavelet coefficients using (6) to obtain the modified wavelet coefficients.

(iv) Perform inverse wavelet transform on the modified coefficients to obtain the denoised estimate image $\hat{X}$.

3 Experimental Results

Our experiments have been carried out on the noisy images, which include Lena, Mandrill, and Barbara (refer Fig. 1). Different noise levels: 10, 20, 30, 50, 75, and 100 are generated by adding Gaussian white noise to the original noise-free images. We take three, four, and five levels of wavelet decompositions using the Symlet wavelet with a vanishing moment of eight. We have computed the results by using NeighShrink, IAWDMBNC, IIDMWT, and our proposed methods in terms of PSNR (in db) for test images using two different window sizes: 3×3 and 5×5. The results for decomposition levels: three, four, and five are shown in Tables 1-3. For the purpose of visual quality, we have taken noisy image with noise level 50 and 10 of Lena and Goldhill (refer Figs. 2(a) and 3(a)) and the noise free images obtained by applying the considered denoising methods (refer Figs. 2(b)-2(i) and 3(b)-3(i)) for the decomposition level three, respectively. We have also shown these PSNR values graphically in Fig. 4(a) for 3×3 window size and Fig. 4(b) with 5×5 window size for decomposition level three only.

We observe that the results of our proposed method are better than that of the NeighShrink, IAWDMBNC, and IIDMWT for all test images, noise, and decomposition levels, for window size 3×3 (refer Tables 1-3, Figs. 2, 3 & 4(a)). For window size 5×5, our results are better for almost all noise levels and for all decomposition levels for Lena image (refer Tables 1-3, Figs. 2(b)-2(i)). We observe that our method outperforms the NeighShrink, IAWDMBNC and IIDMWT for all noise and decomposition levels in window size 5×5 for Mandrill (refer Tables 1-3, Figs. 3(b)-3(i)). For window size 5×5, our results are better for almost all noise levels and for all decomposition levels for Barbara (refer Tables 1-3, Figs. 4(b)). It is evident from tables 1-3 and Figs. 2, 3 & 4 that our method removes noise significantly as compared to the NeighShrink, IAWDMBNC and IIDMWT for window size 3×3. For window size 5×5, it removes noise significantly for higher noise level as compared to the NeighShrink, IAWDMBNC and IIDMWT; but it does not remove noise for low noise level. Similar results were obtained for other images also. We however have given the numerical results for all images in tables 1-3.

Table 1: PSNR (in db) for images: Lena, Mandrill, and Barbra with noise levels: 10, 20, 30, 50, 75, and 100 for NeighShrink, IAWDMBNC, IIDMWT and our proposed method with decomposition level three (3)

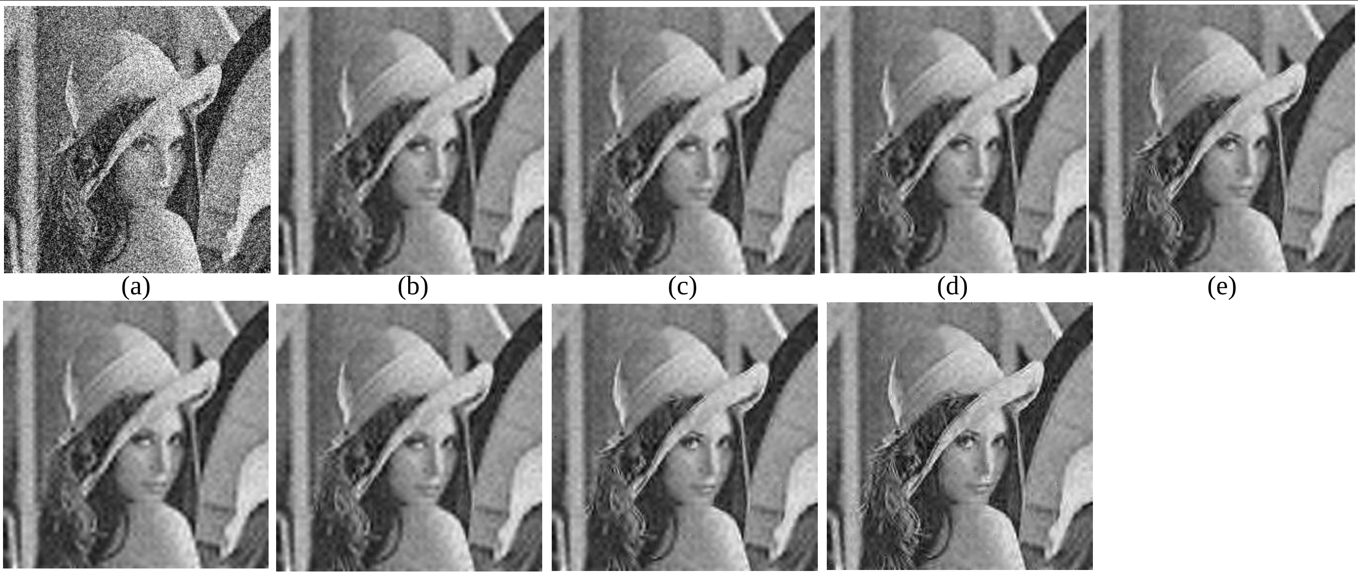
Images	Noise levels	Denoise Methods with decomposition level:3							
		NeighShrink		IAWDMBNC		IIDMWT		Proposed	
		3x3	5x5	3x3	5x5	3x3	5x5	3x3	5x5
Lena	10	33.23	34.25	33.83	33.34	33.65	33.84	34.20	32.53
	20	28.73	30.37	29.69	30.53	29.28	30.77	30.85	30.03
	30	26.54	27.65	27.30	28.43	26.98	28.16	28.55	28.81
	50	24.85	25.11	25.24	25.85	24.93	25.40	25.95	26.46
	75	23.91	23.91	23.96	24.03	23.91	23.91	24.13	24.49
	100	22.89	22.89	22.87	22.85	22.89	22.89	22.90	22.92
Mandrill	10	27.26	29.64	28.52	29.78	27.91	29.84	29.13	29.99
	20	21.96	24.32	22.83	25.13	22.51	24.93	23.94	25.64
	30	20.38	21.41	20.83	22.37	20.62	21.96	21.85	23.25
	50	19.81	19.89	19.93	20.16	19.84	20.00	20.22	20.98
	75	19.51	19.51	19.51	19.54	19.51	19.51	19.57	19.75
	100	19.11	19.11	19.10	19.10	19.11	19.11	19.10	19.15
Barbara	10	31.06	32.52	31.83	32.37	31.61	32.39	32.32	31.97
	20	25.35	27.64	26.37	28.27	26.02	28.11	27.37	28.48
	30	22.87	24.54	23.77	25.51	23.20	25.12	24.65	26.23
	50	21.98	22.14	22.19	22.82	22.04	22.27	22.63	23.55
	75	21.46	21.46	21.49	21.59	21.46	21.47	21.59	21.91
	100	20.85	20.85	20.84	20.87	20.85	20.85	20.86	20.96

Table 2: PSNR (in db) for images: Lena, Mandrill, and Barbra with noise levels: 10, 20, 30, 50, 75, and 100 for NeighShrink, IAWDMBNC, IIDMWT and our proposed method with decomposition level four (4)

Images	Noise levels	Denoise Methods with decomposition level:4							
		NeighShrink		IAWDMBNC		IIDMWT		Proposed	
		3x3	5x5	3x3	5x5	3x3	5x5	3x3	5x5
Lena	10	33.22	34.25	33.83	33.35	33.65	33.48	34.20	32.53
	20	28.58	30.39	29.64	33.56	29.22	30.82	30.90	30.03
	30	26.09	27.58	27.07	28.50	26.74	28.22	28.64	28.88
	50	23.47	24.60	24.47	25.71	24.01	25.18	26.02	26.71
	75	22.52	22.93	22.96	23.66	22.77	23.28	24.14	24.93
	100	22.06	22.09	22.51	22.76	22.17	22.36	22.97	23.58
Mandrill	10	27.26	29.64	28.52	29.78	27.91	29.48	29.13	29.99
	20	21.90	24.32	22.80	25.13	22.48	24.93	23.94	25.64
	30	20.12	21.38	20.66	22.37	20.47	21.95	21.85	23.26
	50	19.37	19.59	19.60	20.02	19.46	19.83	20.13	21.01
	75	19.14	19.20	19.24	19.40	19.14	19.29	19.47	19.84
	100	19.04	19.04	19.05	19.13	19.04	19.04	19.17	19.36
Barbara	10	31.05	32.52	31.83	32.37	31.60	32.39	32.32	31.97
	20	25.24	27.64	26.32	28.27	25.96	28.12	27.38	28.49
	30	22.57	24.45	23.59	25.51	23.01	25.10	24.66	26.25
	50	21.07	21.74	21.60	22.67	21.36	22.06	22.59	23.63
	75	20.39	20.54	20.76	21.09	20.48	20.92	21.38	22.08
	100	20.18	20.22	20.37	20.44	20.20	20.26	20.68	21.13

Table 3: PSNR (in db) for images: Lena, Mandrill, and Barbra with noise levels: 10, 20, 30, 50, 75, and 100 for NeighShrink, IAWDMBNC, IIDMWT and our proposed method with decomposition level five (5)

Images	**Noise levels**	**Denoise Methods with decomposition level:5**							
		NeighShrink		**IAWDMBNC**		**IIDMWT**		**Proposed**	
		3x3	**5x5**	**3x3**	**5x5**	**3x3**	**5x5**	**3x3**	**5x5**
Lena	10	33.21	34.25	33.83	33.35	33.65	33.84	34.20	32.53
	20	28.55	30.38	29.63	30.56	29.20	30.81	30.90	30.04
	30	26.00	27.57	27.01	28.50	26.70	28.20	28.64	28.88
	50	23.00	24.43	24.27	25.67	23.76	25.12	26.01	26.71
	75	21.22	22.36	22.27	23.47	21.89	22.99	24.08	24.95
	100	20.12	20.86	21.27	22.26	20.60	21.66	22.71	23.62
Mandrill	10	27.25	29.64	28.52	29.78	27.91	28.84	29.13	29.99
	20	21.89	24.32	22.80	25.13	22.48	24.93	23.94	25.64
	30	20.07	21.37	20.64	22.36	20.45	21.95	21.85	23.26
	50	19.16	19.50	19.49	20.00	19.32	19.79	20.12	21.01
	75	18.71	19.00	19.05	19.36	18.82	19.17	19.43	19.84
	100	18.58	18.70	18.79	19.05	18.61	18.77	19.11	19.39
Barbara	10	31.05	32.52	31.83	32.37	31.60	32.39	32.32	31.97
	20	25.24	27.64	26.32	28.27	25.96	28.12	27.38	28.49
	30	22.53	24.45	23.58	25.50	22.99	25.10	24.66	26.25
	50	20.73	21.69	21.46	22.66	21.17	22.04	22.58	23.63
	75	19.43	20.11	20.10	20.98	19.90	20.71	21.32	22.09
	100	18.82	19.19	19.32	20.10	19.07	19.68	20.49	21.12



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

(f) (g) (h) (i)

Fig. 2: Comparative performance of various denoising methods on Lena with noise level 50 (a) Noisy image with noise level 50; Denoised image using NeighShrink with window size (b) 3×3, (c) 5×5; Denoised image using IAWDMBNC with window size (d) 3×3, (e) 5×5; Denoised image using IIDMWT with window size (f) 3×3, (g) 5×5; Denoised image using Proposed method with window size (h) 3×3, (i) 5×5 for decomposition level three (3)

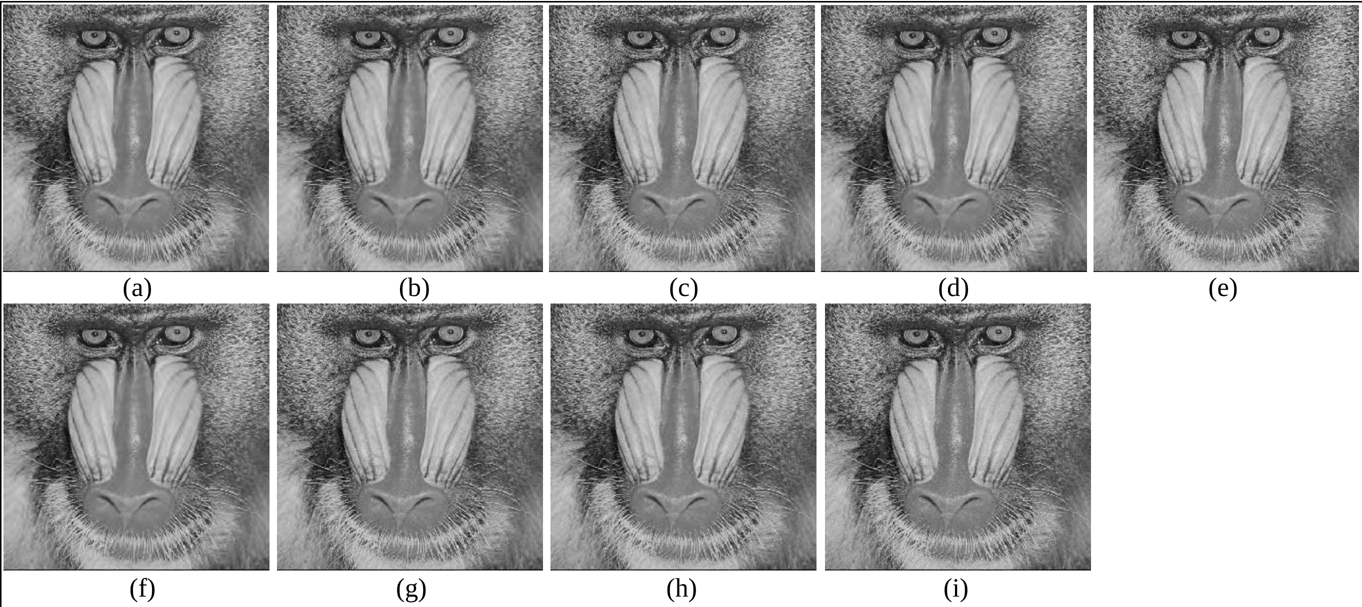
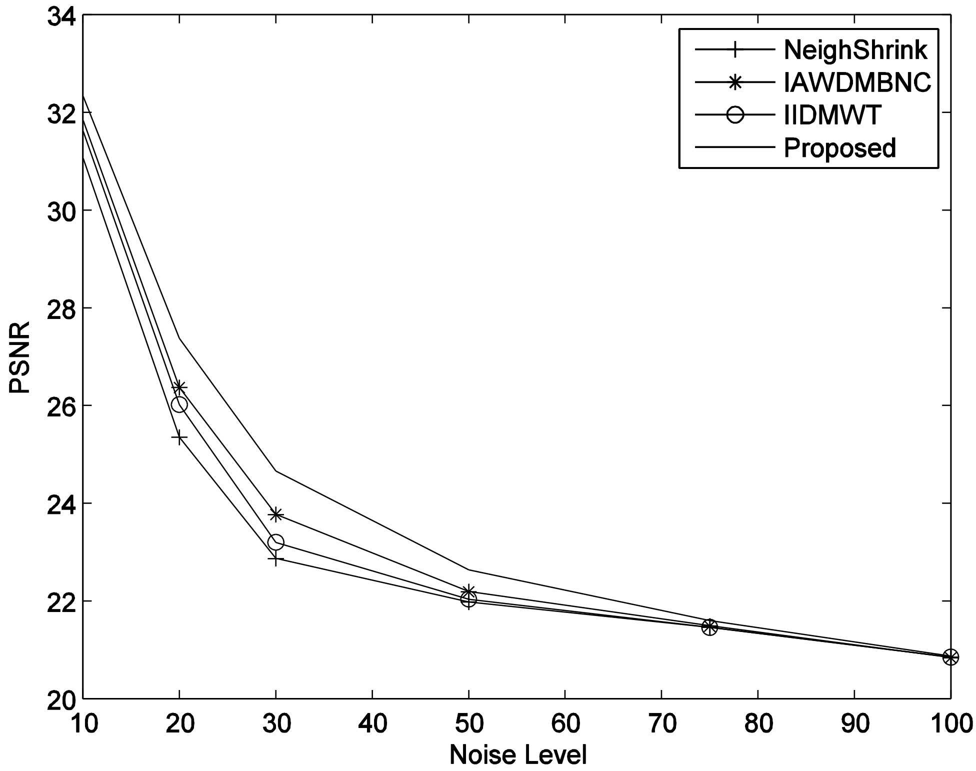
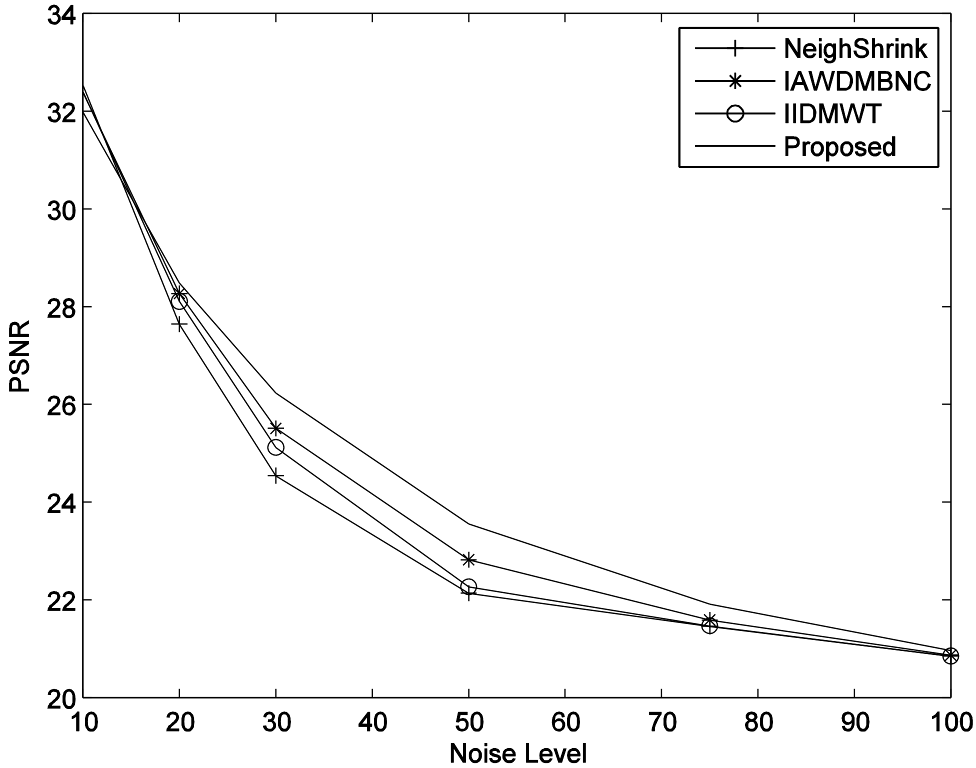


Fig. 3: Comparative performance of various denoising methods on Mandrill with noise level 10 (a) Noisy image with noise level 10; Denoised image using NeighShrink with window size (b) 3×3, (c) 5×5; Denoised image using IAWDMBNC with window size (d) 3×3, (e) 5×5; Denoised image using IIDMWT with window size (f) 3×3, (g) 5×5; Denoised image using Proposed method with window size (h) 3×3, (i) 5×5 for decomposition level three (3)



(a)



(b)

Fig. 4: PSNR gain vs. Noise level of the proposed, NeighShrink, IAWDMBNC, and IIDMWT methods for Barbara image with window size: (a) 3×3 and (b) 5×5 for decomposition level three (3)

4 Conclusion

We have proposed an adaptive image denoising technique that succeeds in removing the noise from an image. This method is completely a data-driven that improves the visual quality of a noisy image considerably and preserves the image details. Simulation results show that our proposed method outperforms over the NeighShrink, IAWDMBNC, and IIDMWT denoising methods.

References:

[1] A. Graps, "An Introduction to Wavelets," IEEE Computational Science and Engineering, Vol. 2, No. 2, 1995.

[2] T. Edwards, "Discrete Wavelet Transforms: Theory and Implementation," Discrete Wavelet Transforms, Stanford University, 1992.

[3] D. L. Donoho and I. M. Johnstone, "Ideal spatial adaptation via wavelet shrinkage," Biometrika, Vol. 81, No. 3, 1994, pp. 425- 455.

[4] D. L. Donoho, "De-Noising by Soft Thresholding," IEEE Transaction Information Theory, Vol. 41, No. 3, 1995, pp. 613–627.

[5] D. L. Donoho and I. M. Johnstone, "Adapting to Unknown Smoothness via Wavelet Shrinkage," Journal of American Statistical Association, Vol. 90, No. 432, 1995, pp. 1200-1224.

[6] T. T. Cai and H. H. Zhou, "A Data-Driven Block Thresholding Approach To Wavelet Estimation," Annals Statistics, Vol. 37, No. 2, 2009, pp. 569–595.

[7] G. Y. Chen and T. D. Bui., "Multiwavelets Denoising Using Neighboring Coefficients," IEEE Signal Processing Letters, Vol. 10, No. 7, 2003, pp. 211-214.

[8] G. Y. Chen, T. D. Bui and A. Krzyzak, "Image Denoising Using Neighbouring Wavelet Coefficients," ICASSP, 2004, pp. 917-920.

[9] J. Jiang, J. Guo, W. Fan, and Q. Chen, "An Improved Adaptive Wavelet Denoising Method Based on Neighboring Coefficients (IAWDMBNC)," World Congress on

Intelligent Control and Automation, China, 2010, pp. 2894-2898.

[10] H. Om and M. Biswas, "An Improved Image Denoising Method based on Wavelet Thresholding (IIDMWT)," Journal of Signal and Information Processing (USA), Vol. 3, No. 1, 2012, pp.109-116.

[11] Y. Yang and Y. Wei, "Neighboring Coefficients Preservation for Signal Denoising," Circuits, Systems, and Signal Processing, Vol. 31, No. 2, pp. 827-832, 2012.