An Improved Adaptive Wavelet Thresholding Image Denoising Method

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ABSTRACT
The NeighShrink, IAWDMBNC, and IIDMWT are some familiar methods for noise minimization from corrupted image. However, this mentioned method suffers from optimal recovery of the original image since the threshold value does not minimize the noisy wavelet coefficients across the image scale factor. In this paper, we propose an improved denoising method that provides an adaptive way of setting up minimum threshold by shrinking the wavelet coefficients so as to overcome the above problem using a new modified exponential function. The experimental analysis qualifying image such as Peak to Signal Noise ratio (PSNR) and Structural Similarity Index Measure (SSIM) are found better than the NeighShrink, IAWDMBNC, and IIDMWT methods. Moreover, our method retains the original image information with high visual quality.

Keywords
Image noise; Wavelet transform; Thresholding; PSNR; SSIM

1. INTRODUCTION
During acquisition and transmission images get corrupted with noise. Noise removal is an important factor to extract useful information [1]. Recently, some researchers have studied the dependency between wavelet coefficients and shrinking them has been shown to be a useful technique for image denoising especially for Additive White Gaussian Noise (AWGN) [2-3], wherein, the image is decomposed into sub- bands and the noisy coefficients are suppressed using hard or soft thresholding [4]. The soft and hard thresholding involve forcing to zero the coefficients with amplitudes lower than the selected threshold, and preserving (in hard) or shrinking (in soft) the coefficient greater in magnitude than this threshold with the threshold value. One of the trusted and most widely used thresholding techniques is VisuShrink [5-6], which performs thresholding by using term-by-term concept. Other two important methods that take the neighboring coefficients into account are NeighCoeff and NeighBlock methods [7].

Chen and Bui showed improvement with use of the neighbouring wavelet thresholding idea of multi-wavelet which outperforms the neighbouring coefficients based single wavelet denoising method for real-life images [8-9]. Latha et al. have extended the Chen et al. method using the threshold of VisuShrink and shrinkage factor as JS rule used in NeighShrink, an image denoising scheme by considering a square neighborhood in the wavelet domain [10]. Mohideen et al. have developed ModiNeighShrink that improves the NeighShrink by using their shrinkage factor [11].

We have further improved the ModiNeighShrink method by developing an improved threshold of universal threshold (IIDMWT) that outperforms over NeighShrink and ModiNeighShrink [12] derived based on Mantosh Biswas et al,. In [13], Jun Jiang et al. have discussed an adaptive denoising algorithm based on new threshold and shrinkage factor (IAWDMBNC). Krishna veni et al., improved wavelet thresholding [15] using adaptive method and obtained better results. The experimental results show that the neighboring coefficients based methods have advantages over the traditional term-by-term wavelet denoising methods. These methods which are based on Cai et al. approach simultaneously either kill or keep all the coefficients in groups.

In literature we could see lots of new techniques for image noise minimization. However, setting a suitable threshold for noise minimization remains critical issue. The proposed image denoising method exploits the minimum threshold from the sub-band size with improving factor for wavelet coefficients using the shrinkage factor of the NeighShrink. The results obtained with the proposed method in terms of PSNR and SSIM shows improvement over NeighShrink, IAWDMBNC, and IIDMWT methods. The organization of the paper is as follows. Section 2 discusses the background and basic principle used in related existing methods. Section 3 presents our proposed work with improved threshold factor. The experimental results are discussed in section 4 and concluded with future scope in section 5 followed by references.

2. BACKGROUND
Suppose that a given original image, S, has been corrupted by additive Gaussian white noise, Z, with independent identical distribution (i.i.d) i.e. M (0, σ2). The corrupted image X is defined as:

$$X = S + Z \qquad (1)$$

The number of pixels in the original image is 2M and it is of M * M size ($1 \le m, n \le M$).

Our goal is to denoise the noisy image X in order to estimate an image Sˆ as close as possible to original image S in the sense of the mean squared error (MSE). There are various methods for threshold evaluation that shrink the noisy coefficients. The VisuShrink uses the threshold function, denoted by T1, which is proportional to the standard deviation of the noise [6]. This threshold is also referred as universal threshold and is given as:

$$T_1 = \sigma \sqrt{2 \log M} \qquad (2)$$

Where σ2 represents the noise variance which is defined based on the median absolute deviation as follows:

$$\sigma^2 = [\text{median} \mid X(m,n) \mid / 0.6745]^2 \qquad (3)$$

Where, X (m,n) € HH1.

The VisuShrink method however yields an overly smoothed image since the threshold estimation is derived under the constraint with high probability. The modified threshold, denoted by T2, overcomes this shortcoming [12], which is given as:

$$T_2 = \sigma \sqrt{2 \log \hat{M}} \quad (4)$$

Where, $\hat{M} = \frac{M}{2^k}$ is an image dimension at k^{th} decomposition level.

The NeighShrink incorporates neighbouring coefficients in thresholding estimation [8-10]. This method groups the wavelet coefficients in non-overlapping blocks and then thresholds them empirically block-wise. Let $Sq^2_{m,n}$ be the summation of square of wavelet coefficients, denoted by $d_{p,q}$. We have

$$Sq^2_{m,n} = \sum_{(p,q) \in B_{m,n}} d^2_{p,q} \quad (5)$$

Where, B m,n represents the neighboring window in the sub-band. For every wavelet coefficient d p,q of interest, we need to consider a square neighboring window B m,n of size N * N centered at that pixel (Fig. 1). Here N requires odd otherwise there will not be a unique central pixel in the window. We shrink the wavelet coefficients using the following formula on neighboring coefficients:

$$\text{Estimate}(S_{m,n}) = X_{m,n}\{(1 - T1^2 / sq^2_{m,n})+\} \quad (6)$$

Here '+' sign at end of formula refers to keep the positive value and for negative set it to zero.

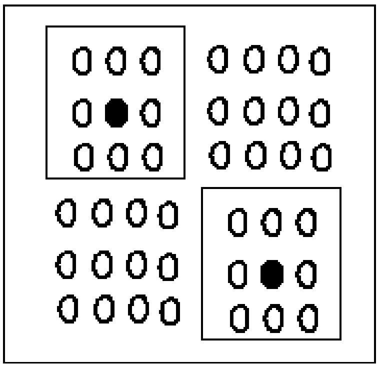

Fig. 1. Neighborhood window centered at the wavelet coefficient to be shrunk

Using the above method to the noisy wavelet coefficients, some details in the image are lost and sometimes the reconstructed image becomes blurred because this method kills more noisy coefficients due to its very large threshold. The IIDMWT method overcomes this problem by using the following shrinkage factor [12]:

$$\text{Est.}(S_{m,n}) = X\ m,n\ \{ (1 - (3/4) * (t^2_2 / Sq^2\ m,n) \} \quad (7)$$

Another method, namely, IAWDMBNC that improves NeighShrink method takes several useful values on the neighboring coefficients, which are defined as [13]:

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

$$Sq_{min} = \min(Sq^2_{m,n}) \quad (8)$$

Here Sq_{max} and Sq_{min} represent maximum and minimum values of Sq^2 m,n, which is defined in (5). In this method, the adaptive threshold is calculated as follows:

$$T_{m,n} = (T1)\{ (Sq_{max} - Sq_{m,n}) / (Sq_{max} - Sq_{min}) \} \quad (9)$$

Now, shrink the wavelet coefficients using the following expression:

$$\text{Est.}(S_{m,n}) = X_{m,n}\{1 - ((T^2_{m,n}) / (Sq^2_{m,n}))\}_+ \quad (10)$$

3. PROPOSED METHOD

In the NeighShrink method, the detailed features of the signal are over-smoothed since its threshold is too large. This problem has been overcome in the IAWDMBNC and IIDMWT methods by using the modified adaptive threshold and shrinkage factor. These methods, however, are not able to remove noise efficiently as they remove many coefficients because of absolute large threshold value. Therefore, we try to overcome this shortcoming by modifying all the detailed noisy coefficients using the exponential function which leads to the exponential decay of the wavelet coefficients across scales. Therefore, a new improved factor f(t) is applied to the adaptive threshold [15], that removes the noise efficiently.

3.1. Estimation of Threshold

The new threshold, T_{NEW} is defined as follows:

$$T_{NEW} = f(t).\ \sigma$$

$$T_{NEW} = f(t) * \sigma \sqrt{2 \log M' - k} \quad (11)$$

Here, f(t) is an improved factor substituted, defined as: f(t) = ; t>0 is an integer in lieu with Mantosh Biswas et al., substation of with t>0. For instance at t=2, the proposed f (t) = 0.624 while Mantosh Biswas et al., method gives 0.511 which apparently proves that the proposed factor will fit better to the thresholding factor.

3.2. Algorithm

The steps of the proposed algorithm are given as:

Input: 512 x 512 scale image corrupted with different noise variances

Output: Noise minimized reconstructed image

Begin

i. Perform 2-D Discrete Wavelet transform on noisy image up to K^{th} decomposition level.

ii. For each decomposition levels of the details subband (i.e. HH, HL, and LH) with the wavelet coefficients

Do

- Calculate the new threshold, T_{NEW} using (11) with new improved f(t).
- Apply the shrinkage factor given in (6) to obtain the noiseless wavelet coefficients.

End

iii. Repeat steps (i) and (ii) for all decomposition levels.

iv. Apply inverse discrete wavelet transform to reconstruct the noise minimized image.

End

4. SIMULATION RESULTS

In our experiments, we have taken four gray scale images: Lena, Mandrill, Barbara, and Cameraman, each of size 512 × 512 (ref. Fig. 2). These images are corrupted by different levels of white Gaussian noise: 10, 20, 30, 50, 75, and 100. The Symlet wavelet of length eight and the four decomposition levels are considered. To investigate effectiveness of the noise suppression and to evaluate visual quality, the most common parameter PSNR is used. The results of PSNR's are shown for NeighShrink, IAWDMBNC, IIDMWT, and our proposed method with t= 2 by taking 3×3 window sizes (ref. Table I). It is evident from the results that the proposed method gives better performance in terms of PSNR than the methods: NeighShrink, IAWDMBNC, and IIDMWT, for all the test images: Lena, Mandrill, Barbara, and Cameraman. Moreover, we have shown the comparison of the proposed method using t=2with the denoising methods: NeighShrink, IAWDMBNC, and IIDMWT, for the Barbara corrupted by noise level 50 (ref. Fig. 3). It is evident from these figures that our proposed method has better visual quality than the NeighShrink, IAWDMBNC, IIDMWT and Mantosh Biwas et al., denoising methods.

5. CONCLUSION

In this paper, we have presented a new improvement in thresholding that impose positive effects on the denoising algorithm that eliminates the noise from the noisy image in a significant manner. We also find that the experimental results of PSNR in our proposed method are higher than the NeighShrink, IAWDMBNC, IIDMWT and Mantosh Biswas et al., methods. Thus, the resultant visual quality of the noise-free image improves significantly over noisy image.

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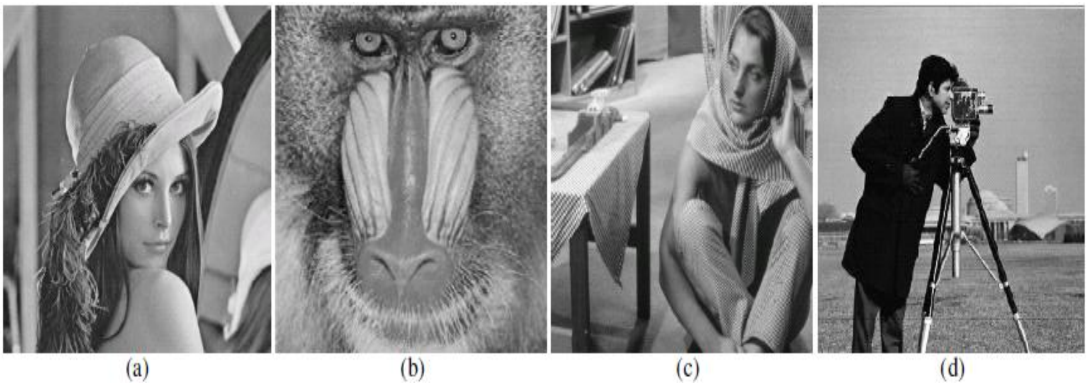

Fig. 2. Original test images (each of size 512×512 pixels): (a) Lena (b) Mandrill (c) Barbara and (d) Cameraman

(a)Noisy Image (variance= 50) **(b) PSNR=21.** **(c) PSNR=21.6**

(d)PSNR = 21.36 **(e) PSNR= 21.8** **(f) PSNR = 22.42**

Fig. 3. Comparative performance of various methods on Barbara with noise level 50 (a) Noisy image with noise level 50; (b) Denoised image using NeighShrink; (c) Denoised image using IAWDMBNC; (d) Denoised image using IIDMWT; (e) Denoised image using Mantosh Biswas et al with: t=2 (f) Denoised image using Proposed method with: t=2.

Table 1: PSNR Comparison chart of our proposed method with other state of art methods

Images	**Noise levels**	**PSNR Values for various denoising methods**				
		NeighShrink	**IAWDMBNC**	**IIDMWT**	**Mantosh Biswas et al; (t=2)**	**Proposed method (t=2)**
Lena	10	33.22	33.83	33.65	34.25	34.874
	20	28.58	29.64	29.22	30.08	30.704
	30	26.09	27.07	26.74	27.56	28.184
	50	23.47	24.47	24.01	24.8	25.424
	75	22.52	22.96	22.77	23.12	23.744
	100	22.06	22.51	22.17	22.43	23.054
Average		**25.99**	**26.75**	**26.43**	**27.04**	**27.66**
Mandrill	10	27.26	28.52	27.91	29.43	30.054
	20	21.9	22.8	22.48	23.66	24.284
	30	20.12	20.66	20.47	21.22	21.844
	50	19.37	19.6	19.46	19.7	20.324
	75	19.14	19.24	19.14	19.25	19.874
	100	19.04	19.05	19.04	19.04	19.664
Average		**21.14**	**21.65**	**21.42**	**22.05**	**22.67**

Barbara	10	31.05	31.83	31.6	32.41	33.034
	20	25.24	26.32	25.96	26.93	27.554
	30	22.57	23.59	23.01	23.9	24.524
	50	21.07	21.6	21.36	21.8	22.424
	75	20.39	20.76	20.48	20.83	21.454
	100	20.18	20.37	20.2	20.31	20.934
Average		**23.42**	**24.08**	**23.77**	**24.36**	**24.99**
Cameraman	10	32.7	33.29	33.3	33.89	34.514
	20	26.96	27.76	27.42	28.38	29.004
	30	24.6	25.46	25.04	25.82	26.444
	50	21.9	23.01	22.37	23.21	23.834
	75	20.37	21.11	20.5	21.23	21.854
	100	19.87	20.32	19.88	20.31	20.934
Average		**24.40**	**25.16**	**24.75**	**25.47**	**26.10**