A Comparative Analysis of PSNR value for Images using Wavelet Based Thresholding Methods

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***Abstract*— Thresholding is a process of shrinking the small absolute coefficients value while retaining the large absolute coefficient value. It will produce finer reconstruct signal. Since this method is taking the condition that the amplitude of wavelet transform coefficients signals are much larger than noises, so the unconsidered noise will be removed while holding the significant signal. This paper examine several thresholding methods namely VisuShrink (Hard Threshold), VisuShrink (Soft Threshold), BayesShrink, OTW SURE-LET and NeighShrink SURE. These five methods are implemented on standard test images and medical images to perceive its' different performance based on the Peak Signal-to-Noise Ratio (PSNR) value.**

Keywords*— *Wavelet, Thresholding, Peak Signal to Noise Ratio (PSNR)

I. INTRODUCTION

In image processing field, the reconstructed image is always facing with the noisy, incomplete and blurry problem. From the previous work, we can find some denoising methods mainly on spatial-domain and wavelet-domain filter. Some example for spatial-domain filter are Mean filter, Median filter, Alpha-trimmed filter and Wiener filter. While the Wavelet-domain filters are VisuShrink, SureShrink, BayesShrink, OTW SURE-LET and NeighShrink SURE.

Wavelet-domain filter gains it popularity because it can perceive a signal in different resolution or in different window. Wavelet is a flexible tool with rich mathematic content and has enormous potential in many applications and greatly being used in the field of digital images. Wavelet algorithm work as signal processing in such a way like the human vision do. It provides a much more precisely in digital image, movies, color image and signal. It also has widely used in data compression, fingerprint encoding and also image processing.

II. RELATED WORK

A. *Concept of Thresholding*

In the wavelet transform, the noise energy is distribute in all wavelet coefficients, while the original signal energy is found in some of the coefficients. Therefore, the signal energy is found much larger than noise energy. So, small coefficients can be considered as caused by noise while large coefficients are triggered by significant signal features.

Based on this idea, thresholding process is proposed. Thresholding is a process of shrinking the small absolute coefficients value while retaining the large absolute coefficient value. It will produce finer reconstructed signal. Since this method is taking the condition that the amplitude of wavelet transform coefficients signals are much larger than noises, so the unconsidered noise will be removed while holding the significant signal.

Threshold also can be define as the Peak Absolute Error (PAE) accepted for image reconstruction [1]. Hard and soft threshold are the common operator used in conjunction with DWT. Donoho is the person who first introducing the word 'de-noising' to explain the process of noise reduction in threshold [2].

Donoho reveal the Donoho universal threshold that give the best estimation error in minimun sense. On the other hand, some noise and clean signal will be discarded by thresholding, producing some artifact. As can be seen in Figure 1, eliminating certain coefficient will not harm the signal value. Dotted line in the middle image represent the discarded coefficient value while the solid line is the retained coefficient value.

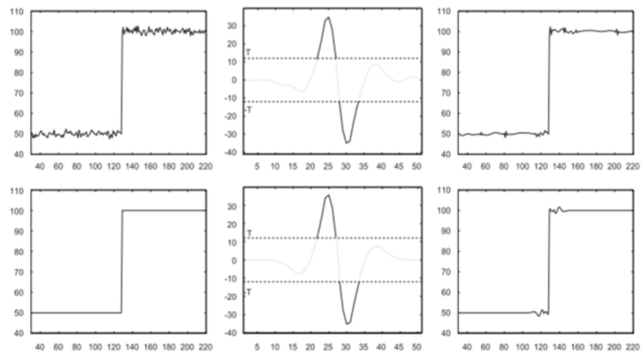

Figure 1: The above image shows the noisy step signal while the below image shows the clean step signal (spine biorthogonal 3/9 wavelet). The left image: signal. The middle image: its wavelet representation. The right image: final result [3].

The wavelet coefficient for hard threshold, H_h, is performed as in equation (1):

$$h_h(i) = \begin{cases} y(i), & |y(i)| > \lambda \\ 0, & others \end{cases} \tag{1}$$

where y(i) is the wavelet coefficients, λ is the specified threshold.

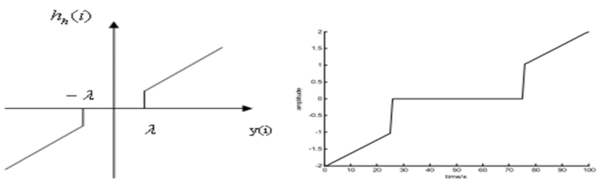

Figure 2: Hard threshold function [4]

In the hard threshold, all the coefficient with higher magnitude than the selected threshold will be retain the same while the rest is set to zero. However, it produce the artifact appearance because of the region created around zero where the coefficients are considered insignificant.

With better image recovery in mind, the soft threshold is proposed to reduce the gap between the remaining and discarded coefficients.

For soft threshold, H_s, the coefficients is expressed as in equation (2):

$$h_s(i) = \begin{cases} \operatorname{sgn}(\ y(i))\left[|y(i)| - \lambda\right], & |y(i)| \geq \lambda \\ 0, & others \end{cases} \tag{2}$$

The elements with absolute value is lower than the threshold value will be set to zero and then the other coefficient will be shrunk. sgn(*) is a sign function. Refer to equation (3)

$$\operatorname{sgn}(\mathrm{n}) = \begin{cases} 1 & \mathrm{n} > 0 \\ -1 & \mathrm{n} < 0 \end{cases} \tag{3}$$

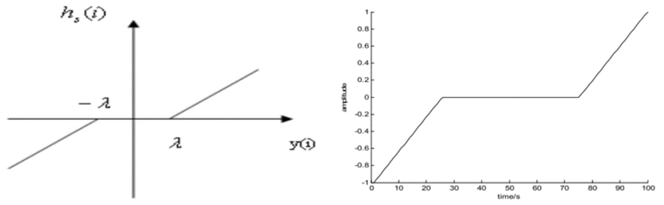

Figure 3: Soft threshold function [4]

In soft thresholding, the coefficient with higher magnitude than the selected threshold will be supressed towards zero while the rest will be set to zero. This activity lead to over smoothing effect at the reconstructed image which will cause a poor PSNR value.

There are two types of thresholding; global and level dependent threshold. Global threshold imply single threshold value globally to all wavelet coefficient while level dependent threshold use different threshold value at different level.

Threshold value estimation is very crucial. If the threshold value set too small, it will adopt noise into the signal. While, if the threshold value is too high, the important coefficients value will be screened out leading to deviation condition [5].

III. Wavelet-Based Thresholding Methods

Donoho and Johnstone have done a lot in wavelet thresholding. They first invented the VisuShrink that using the hard thresholding [6] and soft threshold [2] rules. The universal threshold is defined as equation (4)

$$t = \sigma\sqrt{2\log n} \tag{4}$$

Where the σ is the noise variance present in the signal and n is the number of pixel in the image. For unknown σ, one can be replace by MAD/0.6745, where MAD is median absolute value of the finest scale wavelet coefficients.

The main disadvantage of VisuShrink is it not considering the mean square error, the image is over smoothed, removing too many coefficients and cannot remove the speckle noise. VisuShrink is using the global thresholding scheme where only single threshold value is apply at entire wavelet coefficients.

The BayesShrink [7] method apply subband dependent, which means that threshold value is selected independently at each band of resolution in the wavelet decomposition. It is adaptive with data-driven threshold capability and use merely the same concept with the soft threshold.

The Bayes threshold value, tb in BayesShrink is generated by using Bayesian mathematical framework. It is define as equation (5)

$$t_b = \frac{\sigma^2}{\sigma_s} \tag{5}$$

Where σ^2 is the noise variance and σs is the signal variance without noise.

By using the neighbouring window concept, [8] propose a method called NeighShrink. The wavelet coefficient in different subband is shrinked independently while the threshold and window size is remain unchanged. The wavelet coefficients is thresholded according to the magnitude of the squared sum of all wavelet coefficients, local energy inside the neighbouring window. NeighShrink outstrip the PSNR performance of VisuShrink and SureShrink.

Another popular approach is NeighShrink SURE was proposed by [9]. It is an extended version of NeighShrink where it can determine the optimal threshold and neighbouring window at every subband using Stein's Unbiased Risk Estimate (SURE) where it significantly increase the denoising performance.

[10] have developed the Orthonormal Wavelet Thresholding Stein's Unbiased Risk Estimate Linear Expansion of Threshold (OTW SURE-LET) that also applying the Stein's Unbiased Risk Estimate (SURE) method. It directly parameterize the denoising process with unidentified weights. It also calculating the unidentified weights by solving the linear system equation.

IV. RESULT AND ANALYSIS

Simulation of the wavelet-based thresholding methods are carried out on Matlab R2012a platform. The standard test images with different image format are used to evaluate the differences if any. We use Lena.bmp, Lena.png, Barbara.bmp and Barbara.png of size 512x512.

While for the medical image we use two different breast images (mdb001.pgm and mdb322.pgm) retrieved from MIAS MiniMammographic Database, the database owned by the Mammographic Image Analysis Society and can downloaded for free at http://www.mammoimage.org/databases/. The name 'pgm' is an acronym for 'Portable Gray Map' representing a grayscale graphic image.

Figure 4: Test images with different format. From left to right, top to bottom: Barbara.bmp, barbara.png, lena.bmp, lena.png, mdb001.pgm, mdb322.png.

The methods involve in this comparison are VisuShrink (Hard Threshold) by [6], (Soft Threshold) by [2], BayesShrink [7], OTW SURE-LET [10] and NeighShrink Sure [9].

The experiment are conducted at different Gaussian noise levels, σ = 10, 20, 30, 50, 75 and 100. The objective quality performance of the reconstructed image is measured by Peak Signal-to-Noise Ratio (PSNR) [11]. PSNR is measured in decibel (dB) by equation (6):

$$PSNR = 10\ log_{10} \frac{255^2}{MSE} \quad (6)$$

The value of 255 is the maximum possible value that can be attained by image signal. While Mean Square Error (MSE) is defined by equation (7):

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} ||I(i,j) - K(i,j)||^2 \quad (7)$$

where M*N is the size of the original image while I(i,j) is the original image and K(i,j) is the reconstructed image [12]. The corresponding PSNR value of each method is as shown in Table 1.

TABLE 1: THE PSNR VALUE COMPARISON BETWEEN SOME OF THE THRESHOLDING METHODS

Sigma	VisuShrink (Hard Threshold) [2]	VisuShrink (Soft Threshold) [2]	Bayes Shink [7]	OTW SURE-LET [10]	Neigh Shrink SURE [9]
Barbara.png					
10	28.0734	25.0998	31.1850	**32.16**	30.3021
20	24.1942	22.6653	27.5244	**27.96**	26.1965
30	22.7419	21.8510	25.5076	**25.82**	24.1647
50	21.7765	21.1912	23.1512	**23.72**	22.0281
75	21.1813	20.8225	21.6333	**22.54**	20.6911
100	20.9032	20.6498	20.3091	**21.81**	19.9473
Barbara.bmp					
10	28.0734	25.0998	31.1924	32.16	**33.0243**
20	24.1942	22.6653	27.4829	27.96	**29.0935**
30	22.7419	21.8510	25.5475	25.82	**27.0058**
50	21.7765	21.1912	23.1721	23.72	**24.6326**
75	21.1813	20.8225	21.5865	22.54	**22.9907**
100	20.9032	20.6498	20.2760	21.81	**21.9392**
Lena.png					
10	31.0927	28.5130	33.6145	34.56	**34.7204**
20	28.0496	26.0346	30.4511	31.37	**31.5302**
30	26.4130	24.8472	28.7942	29.56	**29.7023**
50	24.6826	23.7278	26.6195	27.37	**27.4320**
75	23.7762	23.1216	24.4786	25.76	**27.6156**
100	23.2920	22.8546	22.4605	**24.66**	24.4285
Lena.bmp					
10	31.6748	29.1628	34.1733	35.18	**35.3715**
20	28.6492	26.7869	31.0094	31.96	**32.1139**
30	27.0959	25.6808	29.3569	30.15	**30.2758**
50	25.5540	24.6805	27.2772	28.00	**28.0198**
75	24.6234	24.1549	25.2876	**26.41**	26.2386
100	24.2601	23.9365	23.5088	**25.33**	24.9596
Mdb001.pgm					
10	41.0134	39.1770	35.2404	**44.01**	43.6142
20	38.9000	37.1688	30.0515	**41.11**	40.1294
30	37.5293	35.8539	26.8421	**39.25**	37.8705
50	35.9073	34.3290	22.8693	**36.82**	34.8990
75	33.9141	33.5117	19.6410	**35.03**	32.2743
100	33.4531	33.4396	17.3629	**33.73**	30.2543
Mdb322.pgm					
10	41.2931	38.2733	36.0814	**43.76**	43.6303
20	37.4162	35.6519	30.8312	**40.75**	40.0133
30	36.3680	34.5945	27.5011	**38.82**	37.5314
50	34.9893	32.8871	23.3856	**36.25**	34.4289
75	33.1918	31.5393	20.0090	**34.37**	31.9518
100	31.2572	31.2195	17.5932	**33.05**	30.0631

When looking closer to the result, we observe that medical images show a better PSNR value compared to the standard images where the medical images can reach above 40dB while the standard images just can go only up to 35dB.

This is because the medical images is surrounded by the smooth texture of background region and it is usually black in colour. So reconstructing process on this region doesn't degrade much the medical image's PSNR value. From the result in Table 1, it was detected that OTW-SURE LET technique gives the best performance on thresholding process on medical images.

While for the standard images, the PSNR value of the thresholded images were significantly influenced by the image characteristic. The standard image is usually contain rich fine details and edges that spread at entire image. So, this structures may degrade the quality of the reconstructed image.

From the collected data as shown in Table 1, it was observed that the NeighShrink SURE outperform in both lena.bmp as well as lena.png. But the PSNR value by using OTW SURE-LET show the best value on Barbara.png while NeightShrink Sure demonstrate the fine value Barbara.bmp. This result shows that different image format on standard image will affect the PSNR value.

The performance of the PSNR value of each thresholding methods is merely because of its' different way of eliminating the wavelet coefficient. The VisuShrink use the same threshold value that apply globally to the whole image. So, it doesn't consider the different features at different sub-band image. While the zero-zone concept that applied in BayesShrink improve the image quality because of it's efficient Bayes method.

The Stein Unbiased Risk Estimator (SURE) technique that exist in OTW SURE-LET and NeighShrink SURE tend to threshold the wavelet threshold in group and estimated as a sum of squared course coefficient in the block. When this happen, all the wavelet coefficient in different subband is shrinked independently and leading to an optimal thresholding process.

V. CONCLUSION

In this work, comparative analysis of some of the thresholding methods are carried out. According to the experiment, we can see that medical images produce higher PSNR value compared to standard images because it contain lesser texture and details plus having a large smooth background region. Besides, the result shows that same standard image with different format will give different PSNR performance.

Based on five threshold methods tested, NeighShrink SURE shows the best PSNR value for standard images while OTW SURE-LET is the best thresholding method for the medical images.

In short, a research for a more efficient thresholding method is needed to amuse the standard images with rich texture and details.

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REFERENCES

[1] V. P. Baligar, “Low complexity , and high fidelity image compression using fixed threshold method,” vol. 176, pp. 664–675, 2006.

[2] D. L. Donoho, “De-noising by soft-thresholding,” *IEEE Trans. Inf. Theory*, vol. 41, no. 3, pp. 613–627, May 1995.

[3] V. Bruni and D. Ã. Vitulano, “Combined image compression and denoising using wavelets,” *Signal Process. Image Commun.*, vol. 22, pp. 86–101, 2007.

[4] C. Zhen and Y. Su, “Research on Wavelet Image Threshold De-noising,” *2010 Int. Conf. Futur. Power Energy Eng.*, pp. 3–6, Jun. 2010.

[5] A. I. Scott, “Denoising by W avelet Thresholding U sing M ultivariate M inim um D istance Partial D ensity E stim ation,” Rice University, 2006.

[6] D. L. Donoho and I. M. Johnstone, “Adapting to Unknown Smoothness via Wavelet Shrinkage,” pp. 1–28, 1994.

[7] S. G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression.,” *IEEE Trans. Image Process.*, vol. 9, no. 9, pp. 1532–46, Jan. 2000.

[8] G. Y. Chen, T. D. Bui, and A. Krzy, “Image denoising with neighbour dependency and customized wavelet and threshold,” vol. 38, pp. 115–124, 2005.

[9] Z. Dengwen and C. Wengang, “Image denoising with an optimal threshold and neighbouring window,” *Pattern Recognit. Lett.*, vol. 29, no. 11, pp. 1694–1697, Aug. 2008.

[10] F. Luisier, T. Blu, and M. Unser, “A new SURE approach to image denoising: interscale orthonormal wavelet thresholding.,” *IEEE Trans. Image Process.*, vol. 16, no. 3, pp. 593–606, Mar. 2007.

[11] F. Xiao and Y. Zhang, “A Comparative Study on Thresholding Methods in Wavelet-based Image Denoising,” *Procedia Eng.*, vol. 15, pp. 3998–4003, Jan. 2011.

[12] S. J. Pinto and J. P. Gawande, “Performance analysis of medical image compression techniques,” *2012 Third Asian Himalayas Int. Conf. Internet*, pp. 1–4, Nov. 2012.