International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 9, September 2014

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

Wavelet Transform Based On Image Denoising Using Thresholding Techniques

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Abstract: wavelet transforms enable us to represent signals with a high degree of scarcity .This is the principle behind a non-linear wavelet based signal estimation technique known as wavelet denoising. wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. The aim of this project was to study various techniques such as visuShrink, SureShrink, NeighShrink(proposed method) and determine the best one for image denoising. VisuShrink and SureShrink, the thresholding application removes the coefficients that are in significant to some threshold. NeighShrink is an efficient image denoising algorithm based on the decimated wavelet transform (DWT). Its disadvantage is to use a suboptimal universal threshold and identical neighbouring window size in all wavelet subbands. In this paper, an improved method is given, which can determine an optimal threshold and neighbouring window size for every subband by the Stein's unbiased risk estimate (SURE). In NeighShrink, optimal threshold and neighborhood window size in all subbands keep unchanged. In NeighShrink (proposed method), the Optimal threshold and Neighborhood window size in all subbands is changed. In NeighShrink(proposed method) we retain the required information from the removed coefficients by using neighborhood window size and optimal threshold. They threshold the wavelet coefficients in overlapping blocks rather than individually or term by term as VisuShrink or SureShrink.

Keywords: Image denoising, MSE, PSNR, Wavelet transforms, Neighborhood.

I. INTRODUCTION

An image is often corrupted by noise during its acquisition or transmission. The de-noising process is to remove the noise while retaining and not distorting the quality of the processed image .The traditional way of image de-noising is filtering. Recently, a lot of research about non-linear methods of signal de-noising has been developed. These methods are mainly based on thresholding the Discrete Wavelet Transform (DWT) coefficients, which have been affected by additive white Gaussian noise. Simple denoising algorithms that use DWT consist of three steps.

- Discrete wavelet transform is adopted to decompose the noisy image and get the wavelet coefficients.
- These wavelet coefficients are denoised with wavelet threshold.
- Inverse transform is applied to the modified coefficients and get denoised image.

The second step, known as thresholding, is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing threshold, if the coefficient is smaller than threshold, set to zero; otherwise it kept as it is or it is modified. Replacing the small noisy coefficient by zero and inverse wavelet transform on the resulted coefficient may lead to reconstruction with the essential signal characteristics and with less noise.

During the last decade, a lot of new methods based on wavelet transforms have emerged for removing Gaussian random noise from images. The denoising process is known as wavelet shrinkage or thresholding. Both VisuShrink and SureShrink are the best known methods of wavelet shrinkage proposed by Donoho and Johnstone. For VisuShrink, the wavelet coefficients w of the noisy signal are obtained first. Then with the universal threshold T (is the noise level and N is the length of the noisy signal), the coefficients are shrinked according to the soft-shrinkage rule is used to estimate the noiseless coefficients. Finally, the estimated noiseless signal is reconstructed from the estimated coefficients. VisuShrink is very simple, but its disadvantage is to yield overly smoothed images because the universal threshold T is too large.

Just like VisuShrink, SureShrink also applies the soft shrinkage rule, but it uses independently chosen thresholds for each subband through the minimization of the Stein's unbiased risk estimate (SURE) (Stein, 1981). VisuShrink performs better than SureShrink, producing more detailed images.

II. IMAGE DENOISING USING THRESHOLD

2.1 VisuShrink

VisuShrink is proposed by Donoho and Johnstone. This is also called as Universal threshold. VisuShrink is threshold by applying the Universal threshold. This threshold is given by

$t=\sigma\sqrt{2logm}$

where σ is the noise variance and m ia the number ofpixels in the image.

It follows the hard thresholding rule.An esyimate of the noise level σ is defined based on median absolute deviation given by

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$$\sigma = \frac{median\ (\{abs\,(g_{j-1,k}) : k=0,1,......2^{j}-1\})}{0.6745}$$

where $g_{j-1,k}$ corresponds to the detail coefficients in the wavelet transform.

This asymptotically yields a mean square error(MSE) estimate as m tends to infinity. As m increases, we get bigger and bigger threshold, which tends to oversmoothen the image.

2.2 SureShrink.

The SureShrink threshold is developed by Donoho and Johnstone. It is acombination of Universal threshold and SURE threshold. THE goal of SureShrink is to minimize the MSE, defined as

$$MSE=\frac{1}{n^2}\sum_{x,y=1}^{n}(z(x,y)-s(x,y))^2$$

where Z(x,y) is the estimate of the signal, *s*(*x*,*y*) is the original signal without noise and *n* is the size of the signal.

The SureShrink threshold t^* is defined as

$$t^{*}=\min\,(t,\sigma\sqrt{2logm})$$

where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance computed from Equation , and *m* is the size of the image.

In SureShrink, to the find threshold in every subband, i.e., called Subband adaptive thresholding. It is smoothness adaptive, that means unknown function contains abrupt changes or boundaries in the image, the reconstructed image also do.

III. PROPOSED METHOD

Chen *et al*. proposed a wavelet-domain image thresholding scheme by incorporating neighboring coefficients, namely NeighShrink. The method *NeighShrink* thresholds the wavelet coefficients according to the magnitude of the squared sum of all the wavelet coefficients, i.e., the local energy, within the neighborhood window. The neighborhood window size may be 3×3, 5×5, 7×7, 9×9, etc. But, the authors have already demonstrated through the results that the 3×3 window is the best among all window sizes.

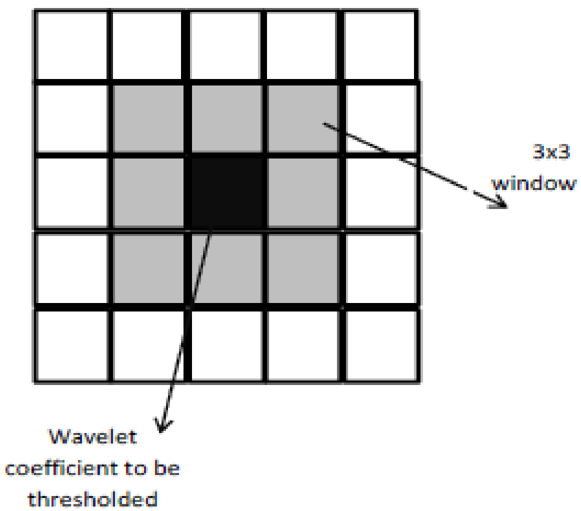

Fig. 3.1: An illustration of the neighboring window of size 3* 3 centered at the wavelet coefficient to be shrinked. The shrinkage function for *NeighShrink* of any arbitrary 3×3 window centered at (i,j) is expressed as:

$$\Gamma_{ij} = [1-\frac{T_u^2}{S_{ij}^2}]$$

where, T_u^2 *is* the **universal threshold** and S_{ij}^2 is the squared sum of all wavelet coefficients in the respective 3×3 window given by:

$$S_{ij}^2 = \sum_{n=j-1}^{j+1}\ \sum_{m=i-1}^{i+1} Y_{m.n}^2$$

Here, + sign at the end of the formula means to keep the positive values while setting it to zero when it is negative. The estimated center wavelet coefficient $\hat{F}_{ij}$ is then calculated from its noisy counterpart Y_{ij} as $\hat{F}_{ij} = \Gamma_{ij}Y_{ij}$

IV. EXPERIMENTAL RESULTS

Fig .4.1: The original test image for Lena with 512x512 pixels.

Fig.4.2: The original test image for Cameraman with 512x512 pixels.

4.1 SIMULATION RESULT FOR LENA

Fig. 4.3: Original image.

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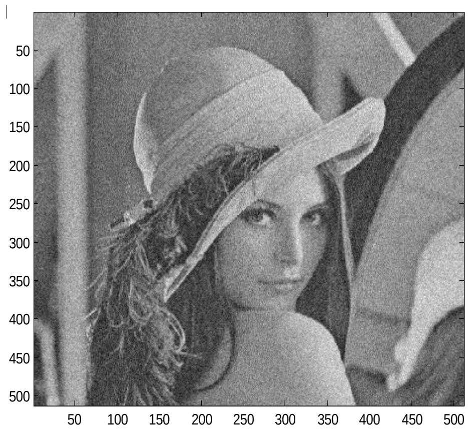

Fig. 4.4: Image affected by Gaussian noise (sigma=20).

Fig. 4.5: Image reconstructed by VisuShrink.

Fig. 4.6: Image reconstructed by SureShrink.

Fig. 4.7: Image reconstructed by NeighShrink (proposed method)

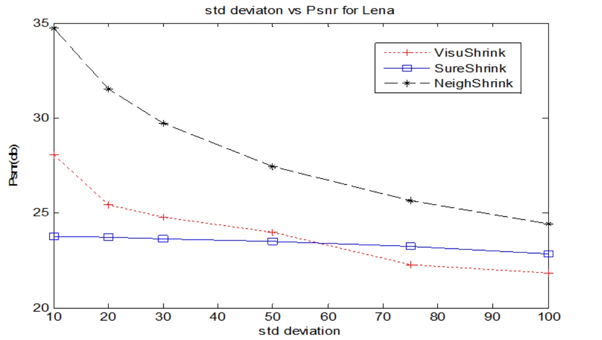

Fig. 4.8: Graph for different std deviation versus psnr for Lena image.

Table 4.1: MSE and PSNR values for Lena image with different std deviation, wtype=db2 and L=4.

σ(std deviation)	VisuShrink		SureShrink		NeighShrink	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
10	115.0718	27.5211	345.5394	22.7458	25.0129	34.1492
20	187.1156	25.4097	346.6324	22.7321	53.4045	30.8550
30	242.7055	24.2800	348.8330	22.7046	80.7713	29.0582
50	324.7123	23.0158	358.1105	22.5906	135.0125	26.8271
75	386.8843	22.2550	378.0739	22.3550	202.6121	25.0641
100	427.9814	21.8166	404.7804	22.0586	266.6778	23.8709

V. CONCLUSION

In this paper, we improve NeighShrink (proposed method) using the Stein's unbiased risk estimate (SURE) by using optimal threshold and neighbouring window size for every wavelet subband instead of using the suboptimal universal threshold and same neighbouring window size in all subbands. From the above experimental results we can conclude that NeighShrink produce good results compare to VisuShrink and SureShrink.

ACKNOWLEDGMENT

The authours would like to thank the reviewers and the associate editor for their constructive comments and suggestions to our paper.

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