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Improved wavelet image denoising technique by cycle spinning and threshold selection

KHELALEF Aziz[1]*, HIMEUR Yassine[2] and BRAHIMI Tahar[2]

[1]Advanced Electronics Laboratory, University of Batna, Batna, Algeria.
[2]Department of Electronics, University of Jijel, Jijel, Algeria.

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ABSTRACT

In this paper, we propose a new wavelet-based image denoising algorithm that is based on a state-of-the-art algorithm, namely FAS (Feature Adaptive Shrinkage). Two modifications are introduced in order to increase its efficiency. This consists of developing a new shrinkage function which is adapted to each level of decomposition. Also, we combined the new scheme with the cycle spinning algorithm in order to resolve the pseudo Gibbs phenomena problem. A number of experiments, carried out on various test images, demonstrate significant improvement over the conventional FAS and against other wavelet denoising methods.

Keywords: Wavelet thresholding, image denoising, shrinkage, wavelet transform, cycle spinning.

*Corresponding author. E-mail: khelalef.aziz@gmail.com.

INTRODUCTION

Nowadays, the wavelet transforms are widely adopted in the literature for image denoising as they efficiently decorrelate the information held in natural images by splitting the signal into high-pass and low-pass subbands (Mallat, 1989; Chang et al., 2000).

The main goal of image denoising is to reduce the degradations that corrupt the image during transmission and creation; in several domain images are corrupted by Gaussian noise and many techniques are proposed to resolve this problem. Wavelet Shrinkage is a useful tool to denoise an image. Since the first works of D. L. Donoho (Coifman and Donoho, 1994; Donoho, 1995) several wavelet thresholding methods were proposed (Kaur et al., 2002; Gupta and Guptaeature, 2007; Dai and Ye, 2007).

In this paper, we propose an improved wavelet thresholding scheme, a new thresholding function adapted to each level of wavelet decomposition will be used, and we will combine the cycle spinning algorithm to improve the denoising technique.

The proposed method is an energy neighboring pixels dependent; those kinds of techniques gives better performance, whereas in standard wavelet methods, the empirical wavelet coefficients shrink pixel by pixel, on the basis of their individual magnitude.

The cycle spinning algorithm proposed by Coifman and Donoho (1994) to resolve pseudo Gibbs phenomena problem of the DWT yields significantly superior image quality and better Peak Signal to Noise Ratio (PSNR), because the original wavelet thresholding of Donoho exhibits visual artifacts and oscillations in the vicinity of signal discontinuities.

This paper is organized as follows: we give an introduction to image wavelet transform, afterwards, we present the proposed scheme; and then we present and compare the simulation result, finally concluding remarks are given in.

IMAGE DISCRETE WAVELET TRANSFORM

The discrete wavelet decomposing (DWT) of an image gives 4 sub bands (1 approximation and 3 details) which is labeled as LL1, LH1, HL1 and HH1. The LL sub band can also be decomposed to a second level of decomposition yielding to LL2, LH2, HL2 and HH2 as shown in Figure 1 (Gnanadurai and Sadasivam, 2006).

The approximation LL comes from low pass filtering

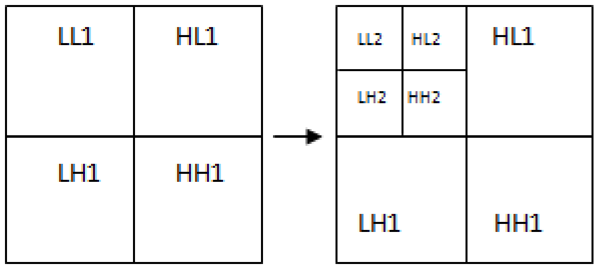

Figure 1. Image decomposition using DWT.

both directions, HL, LH, HH are called detailed, HL comes from low pass filtering in the vertical direction and high pass filtering in the horizontal direction, they are called vertical details, the same for LH (horizontal details), HH (diagonal details) (Gnanadurai and Sadasivam, 200)

Mallat algorithm for image decomposition and reconstruction is shown in Figure 2a and b.

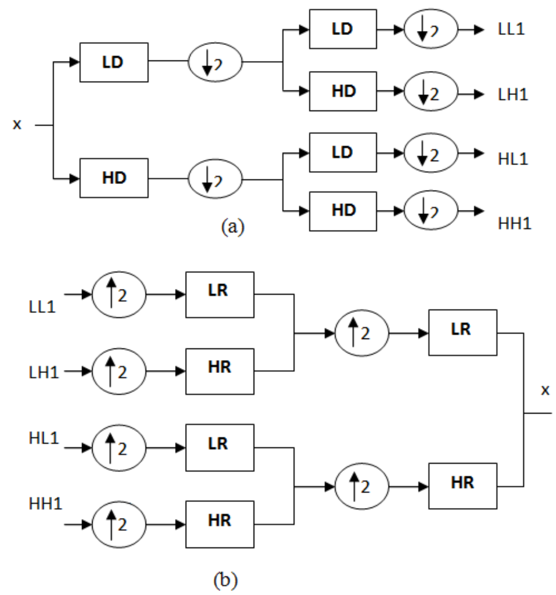

Figure 2. 2-D Mallat algorithm: (a) decomposition, (b) reconstruction.

WAVELET THRESHOLDING

In the case of a Gaussian noise, the problem is how to recover a function f from noisy data g: (Gupta and Gupta, 2007)

$$g = f + \epsilon \quad (1)$$

And $\epsilon \sim N(0, \delta^2)$

The application for DWT on the function g gives:

$$W_g = W_f + W_\epsilon \quad (2)$$

To recover data f from g, all wavelet coefficients W_g are threshold depending on the noise contribution.

Since the famous thresholds function (soft and hard) of Donoho (1995), a lot of thresholding function were proposed.

PROPOSED TECHNIQUE

In Gupta and Gupta (2007), a new wavelet shrinkage denoising algorithm is presented. The algorithm uses Wavelet Transform (WT) to extract information about sharp variation in multiresolution images and applies shrinkage function adapting to the image features. The shrinkage function depends on energy of neighboring pixels, this algorithm suffers from some disadvantages; it uses the same shrinkage function for different level of decomposition which deteriorates the quality of reconstructed image. On the other hand, the wavelet shrinkage algorithms suffer from the pseudo Gibbs phenomena problem. It exhibits visual artifacts and oscillations in the vicinity of signal discontinuities. To overcome these disadvantages we propose two modifications. In the first modification, we propose a new thresholding function as it's shown below, the expression exp(-j/2) preserves the details coefficients of the highest levels of decomposition (levels 2 and 3) yielding to an improvement in the quality of the image and the PSNR results.

$$\hat{d}_{j,k} = \begin{cases} d_{j,k}\left(1-\alpha*\dfrac{\lambda^2}{s^2_{j,k}}\right) & , \text{if } s^2_{j,k} \ge (\beta*\lambda^2)*\exp\left(-\dfrac{j}{2}\right) \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$$s^2_{j,k} = \sum_{m=-r}^{m=r} \sum_{n=-r}^{n=r} d^2_{m,n} \quad (4)$$

$$\lambda^2 = 4.\sigma^2.\log(R) \quad (5)$$

$d_{m,n}$: The pixels in the window
m, n : The central pixel of the window
j: Level wavelet decomposition
α , β: Fixed coefficients ($\alpha = 0.1$ and $\beta = 0.3$)
The window is shown in Figure 3.

σ^2 is the noise variance, which is estimated from the subband HH1, using Formula 2:

$$\sigma^2 = \left[\frac{median\ (|Y_{i,j}|)}{0.6745}\right]^2, Y_{i,j} \in subband\ HH1 \quad (6)$$

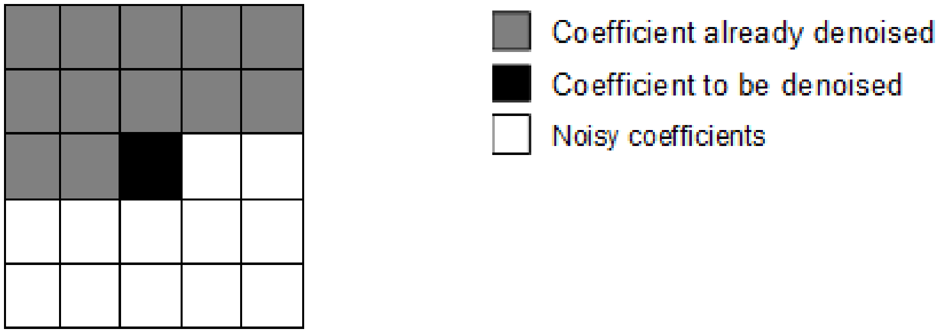

Figure 3. Coefficients' denoising process.

Table 1. PSNR in (dB) obtained by different denoising methods for gray scale image Lena image.

Method	Noise variance				
	10	**15**	**20**	**25**	**30**
Noisy image	28.1538	24.6113	22.0965	20.1931	18.5878
Wiener	33.5508	31.1125	28.9920	27.2295	25.7290
NormalShrink (Kaur et al., 2002)	33.5473	31.6357	30.2804	29.1985	28.3901
BayseShrink (Chang et al., 2000)	33.4404	31.6148	30.3188	29.3731	28.6018
Proposed in Nasri and Nezamabadi-pour (2009)	33.7452	31.8606	30.5670	29.5121	28.7208
Proposed in Yin et al. (2011)	34.4900	32.5900	31.2200	30.1700	29.2900
Proposed in Chuia et al. (2012)	34.5400	32.7700	31.6400	30.8100	30.1400
Proposed in Gupta and Gupta (2007) (original)	33.8706	32.0090	30.6730	29.6702	28.8043
Proposed technique	34.9620	33.0311	31.6578	30.5403	29.7103

Table 2. PSNR in (dB) obtained by the proposed method on different images.

Method	Noise variance				
	10	**15**	**20**	**25**	**30**
Barbara	33.6495	31.2847	29.7233	28.4466	27.4870
Boat	34.0255	31.8362	30.3088	29.1619	28.2272
Cameraman	32.8104	30.3999	28.7095	27.6010	26.6031

In the second improvement we resolve the pseudo Gibbs phenomena problem; by using the cycle spinning algorithm proposed by Coifman and Donoho (1994). This method utilizes the shift variant property of wavelet transform. In this algorithm, by using different shifts of the noisy image, we can compute different estimates of the unknown signal, and then average these estimates.

If we denote the 2-D circular shift by $S_{i,j}$, the wavelet transform by W, and the threshold operator by T, the cycle spinning will be performed as Equation 7:

$$\hat{y} = \frac{1}{k_1 k_2} \sum_{i=1,j=1}^{k_1 k_2} S_{-i,-j} \left(W^{-1}\left(T\left(W\left(S_{i,j}\,(y)\right)\right)\right)\right) \quad (7)$$

Where k_1 and k_2 are the maximum number of shifts which would cause an improvement in denoising.

EXPERIMENTAL RESULTS

The proposed algorithm has been tested on different gray scale images (of size 512 × 512, with 8 bpp). These images were corrupted with different standard deviation of Gaussian noise (σ = 10, 15, 20, 25 and 30). Here, we used 'Daubechies' (Db4) for three levels of wavelet decomposition, the coefficients α and β are fixed at α = 0.1 and β = 0.3 (Gupta and Gupta, 2007), the window size used is 5×5. To evaluate the performance of the proposed technique, the results are compared to different wavelet denoising schemes. Using Peak Signal to Noise

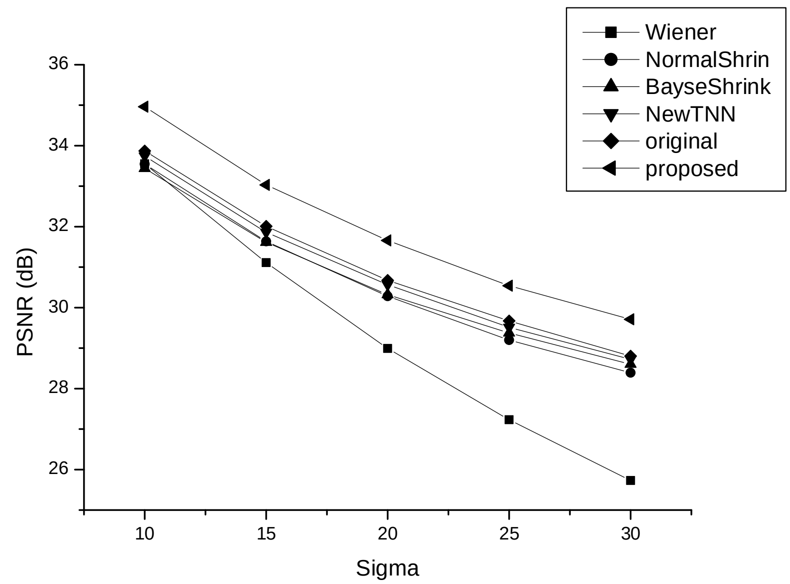

Figure 4. Comparison of denoising performance (PSNR) using six methods for ‘lena’ image.

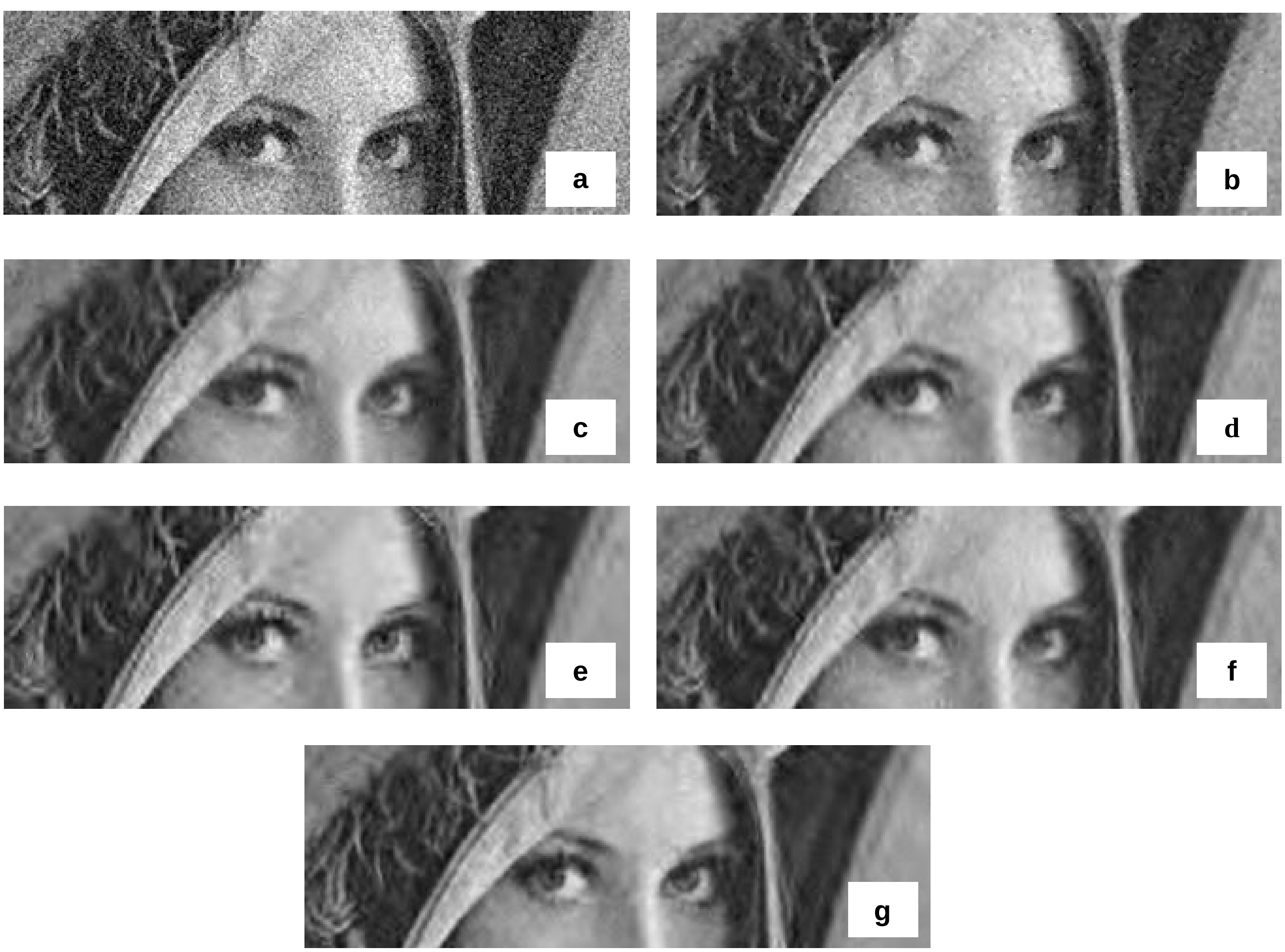

Figure 5. Image denoised using different methods (from top to bottom). (a) Noisy image (σ = 25), (b) Wiener, (c) normalShrink, (d) BayseShrink, (e) New TNN, (f) proposed in Mallat (1989) (original), (g) proposed.

Figure 6. Some gray scale images denoising using the proposed technique. (Left) Noisy image (σ = 25), (Right) proposed technique.

Ratio (PSNR) which is defined by Equations 8 and 9:

$$\mathrm{PSNR} = 10\log_{10}\left[\frac{255^2}{\mathrm{MSE}}\right]\ \mathrm{dB} \qquad (8)$$

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j)-\hat{X}(i,j))^2 \qquad (9)$$

X : Original image.
$\hat{X}$: Denoised image.
M , N : Image dimension.

From the experimental results of the different schemes, Tables 1 and 2 show the superiority of the proposed method against the other techniques for all image test and different standard deviation, PSNR performance (Figure 4) and better image quality (Figures 5 and 6).
The proposed technique shows better details and edges preservation for high noise levels for all images used in simulation.

CONCLUSION

In this paper, we have proposed an improvement of the original technique “Feature Adaptive Wavelet Shrinkage for Image Denoising” proposed in Gupta and Gupta (2007), by using a new wavelet thresholding function adapted to each level instead of the entire tree of the wavelet decomposition and combined with the cycle spinning algorithm to resolve the pseudo Gibbs phenomena problem and improve the denoising process.

The proposed technique gives better visual quality, and PSNR performance for all gray scale images used in simulation.

The future work will base on using neural networks and genetic algorithms to estimate the best threshold.

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