Wavelet Image Denoising Based on Genetic Algorithms and Cycle Spinning Thresholding

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***Abstract*—In this paper a genetic algorithm (GA) based wavelet image denoising method is presented. The proposed scheme introduces a new technique for optimum thresholds selection using genetic algorithms.The optimization of the proposed fitness function yields to optimum thresholds for each subbanb. The cycle spinning algorithm is used in order to reduce pseudo-Gibbs phenomena and improve the denoising performance. Simulation results show that the proposed approach outperform the different methods cited in the literature by giving better image quality and PSNR performance for all benchmark images for different values of standard deviation of the Gaussian noise.**

Keywords; wavelet, image denoising, shrinkage, thresholding, genetic algorithms, DWT.

I. INTRODUCTION

Image denoising is an important step in pre-treatment process; it is one of the most fundamental and widely studied problems in computer vision and image processing [1]. In several domains images are corrupted by Gaussian noise during transmission or acquisition. Image denoising consists of founding a compromise between noise reduction and preservation of the important image features. In this context many methods were proposed. Wavelet Thresholding is a useful tool to denoise an image. Since the first works of D.L. Donoho [2], several wavelet thresholding techniques were proposed.

Earlier, image noise reduction was performing by using filters, generally the denoised images suffer from blurring and edges degradation [3], recently and to resolve filters inability new techniques based on the discrete wavelet transform (DWT) were proposed. Donoho and al. [2] proposed a wavelet image thresholding, where the principal is simple: i) performing the DWT decomposition in different levels, ii) performing a thresholding operation on the details and iii) applying an inverse IDWT to reconstruct the denoised image. The State-of-the-art shows that the methods using a separate threshold for each subband (NormalShrink [4] and BayseShrink [5]) give better image quality and denoising performance than the Level depending scheme called LevelShrink [6] and the original method named VisuShrink [2]. Unfortunately those kinds of methods suffer from threshold selection: using a small threshold yield to destroy image features, big ones can't remove the noise.

Nowadays, and to outperform the conventional DWT techniques, neural networks are used to optimize the thresholds. Zhang in [7] and [8] proposed a space scale adaptive technique called Thresholding Neural Network (TNN) to reduce the Gaussian noise. The TNN is used to obtain the optimized thresholds for Shrinking the DWT (Discrete Wavelet Transform) coefficients stream. In [9] a new TNN subband adaptive image denoising was proposed, where the author propose to use separate TNN for each subband.

The State of the-art shows that the efficiency of a DWT image denoising method depend on the threshold optimization (selection) for each subband of decomposition. Inspired of that, in this paper we propose a new image denoising method based on genetic algorithm and Cycle Spinning [10]. Hence, we used the genetic algorithm to extract optimum thresholds for each subband by minimizing the proposed fitness function, we used the DWT coefficients as the entries of the genetic algorithms blocks, however to resolve pseudo Gibbs phenomena [10] we use a Cycle Spinning thresholding operation.

In this method, we don't have to calculate any derivative functions like in the TNN, also the optimization of all the thresholds is performed at the same time, however in the TNN method each subband is trained singly.

This paper is organized as follows. In section two, we give an introduction to image wavelet transform, next in the third section, we present brief introduction into wavelet thresholding. In the fourth section the proposed technique is described and a discussion with comparisons will be given in section five. Finally, section six contains concluding remarks and perspectives.

II. IMAGE DISCRETE WAVELET TRANSFORM

The discrete wavelet decomposing (DWT) of an image gives 4 subbands (one approximation and tree details) which is labeled as LL1, LH1, HL1 and HH1. The LL subband can also be decomposed to a second level of decomposition yielding to LL2, LH2, HL2 and HH2 as shown below (figure 1) [11]:

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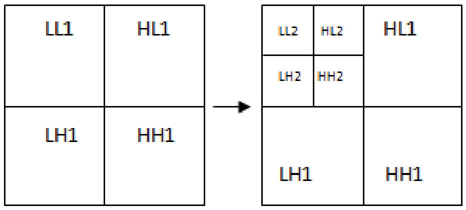

Figure 1. : Image decomposition by DWT.

The approximation LL comes from low pass filtering 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) [11].

Mallat algorithm for image decomposition and reconstruction is shown in figure 2.

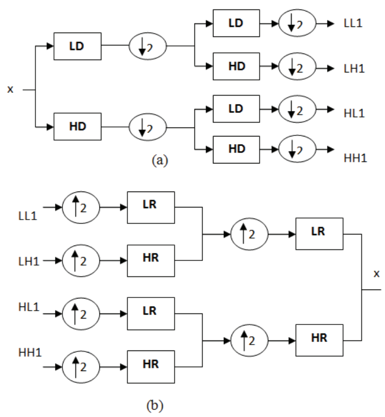

Figure 2. 2-D Mallat algorithm, (a) decomposition, (b) reconstruction.

III. WAVELET THRESHOLDING

In the case of a Gaussian noise, the problem is how to recover a function f from noisy datag [12]:

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

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

The application for DWT on the function g gives:

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

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 [2], a lot of thresholding function were proposed in the denoising image field.

IV. PROPOSED METHOD

Figure 3 shows the diagram of the proposed method in image denoising. The first step in the proposed wavelet thresholding scheme is optimum thresholds recovering using the genetic algorithms, here we use a real genetic algorithm i.e. the chromosomes are not encoded (double vector) and every chromosome is composed of 12 genes, every genes represents a subband threshold.

Figure 3. Structure of the proposed method.

The input of the proposed structure is the noisy DWT subbands coefficients, and the outputs are the optimums thresholds for each subband by minimizing the risk J_{mmse} (mean of the mean square error for each subbands) given as the fitness function for the GA algorithm.

$$J_{mmse} = \frac{1}{P}\sum_{i=1}^{p} MSE_i \qquad (3)$$

and

$$MSE_p = \frac{1}{2N}\sum_{i=1}^{N}(\widehat{V}_i - V_i)^2 \qquad (4)$$

Where:

$p = 1, \dots, P$.

$\widehat{V}_i$: Denoised coefficients.

V_i: Reference coefficients.

p : Subbands.

P : The maximum number of subbands.

From equation (4), it's obvious that we need a reference image to calculate the MSE risk for each subband (p), and because our main problem is to recover the original free noise image i.e., it can't be used. Zhang in [7-8] has proposed a practical solution, to use another noisy image with uncorrelated noise as a reference to calculate the MSE. This assumption is reasonable because in many applications we can receive more than one corrupted image.

The second step in our proposed scheme is cycle spinning thresholding using the optimum thresholds recovered from the GA process. We use the cycle spinning algorithm proposed by Coifman and Donoho [10].Since the first thresholding algorithm proposed by Donoho [2] exhibits visual artifacts and oscillations in the vicinity of signal discontinuities, called pseudo-Gibbs phenomena. 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 (image), and then average these estimates [10].

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:

$$\hat{y} = \frac{1}{k_1 k_2} \sum_{i=1,j=1}^{k_1 k_2} S_{-i,-j}\left(W^{-1}\left(T\left(W\left(S_{i,j}(y)\right)\right)\right)\right) \qquad (5)$$

where k1 and k2 are the maximum number of shifts which would cause an improvement in denoising [10].

The thresholding function used was proposed in [9].It is illustrated by figure 4 and is given by equation 6:

$$\eta(x,\mathrm{thr}) = \begin{cases} x - 0.5\dfrac{\mathrm{thr}^2}{x} & |x| > thr \\ 0.5\dfrac{x^3}{\mathrm{thr}^2} & |x| \leq \mathrm{thr} \end{cases} \qquad (6)$$

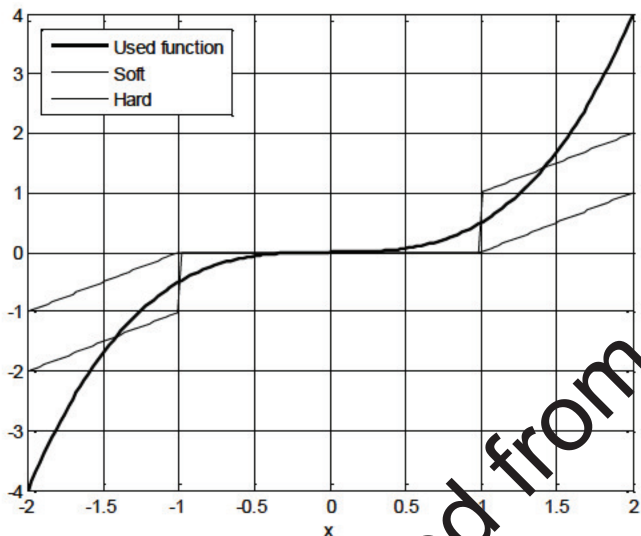

Figure 4. The thresholding function used in the proposed method.

We choose to use this thresholding function because its gives such good proprieties. In [4], the author shows that it's outperform other thresholding functions because it return the coefficients by a polynomial function that increase its capability and leads to better image quality [9].

V. 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 the mother wavelet 'Daubechies' (Db4) with four levels of decomposition, to obtain the optimum thresholds we use a GA with 12 variables with random initial population. The number of generations is fixed bigger enough, to achieve the tolerance function fixed to 1e-9.

To evaluate the performance of the proposed method, the results are compared to different wavelet denoising schemes. In this paper, we used the standard evaluation criterion in Gaussian noise methods that is Peak Signal to Noise Ratio (PSNR) and is defined by [12] :

$$\mathrm{PSNR} = 10\log_{10}\left[\frac{255^2}{\mathrm{MSE}}\right] \ \mathrm{dB} \qquad (7)$$

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j) - \hat{X}(i,j)\right)^2 \qquad (8)$$

X : Original image.

$\hat{X}$: Denoised image.

M , N : Image dimension.

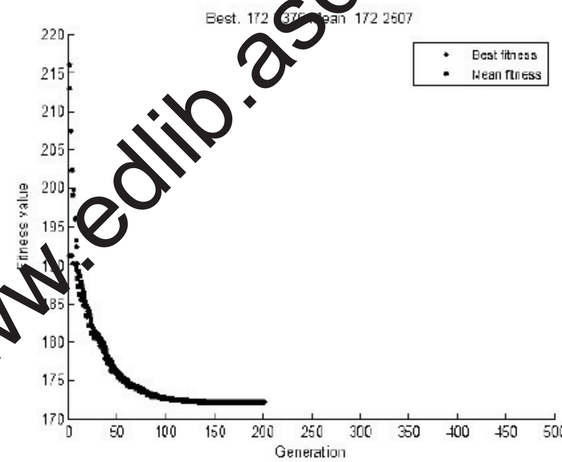

Figure 5. Optimization curves using GA for Lena (with σ = 10).

Figure 5 shows the optimization curve using genetic algorithms on Lena image (σ =10), it's obvious that the fitness function has been minimized yielding to optimum thresholds (shown in table 1) for each subband of the discrete wavelet tree.

TABLE I. OPTIMUM THRESHOLDS FOR LENA IMAGE (STANDARD DEVIATION =10) USING THE PROPOSED TECHNIQUE.

Horizontal	Vertical	Diagonal	Decomposition level
7.1619	13.0998	12.3783	4
18.8501	16.8553	19.5399	3
24.6894	21.5789	25.2529	2
39.4552	31.0881	42.5950	1

TABLE II. PSNR RESULTS FOR VARIOUS DENOISING METHODS ON DIFFERENT BENCHMARK IMAGES.

Image	σ	Noisy	Wiener2	BayseShrink[5]	Zhang [8]	New TNN [9]	Proposed
Lena (512x512)	10	28.1538	33.5508	33.4404	33.6192	33.7452	**34.5502**
	15	24.6113	31.1125	31.6148	31.6885	31.8606	**32.4853**
	20	22.0965	28.9920	30.3188	30.4010	30.5670	**31.0686**
	25	20.1931	27.2295	29.3731	29.3783	29.5121	**30.0327**
	30	18.5878	25.7290	28.6018	28.5555	28.7208	**29.1635**
Barbara (512x512)	10	28.1291	29.7587	31.5230	31.6769	32.0576	**33.0529**
	15	24.6076	28.1547	29.3361	29.3314	29.6381	**30.4931**
	20	22.1232	26.6780	27.7740	27.7191	27.9456	**28.7403**
	25	20.1652	25.3770	26.5559	26.4981	26.6340	**27.4033**
	30	18.5792	24.2290	25.6210	25.6206	25.7363	**26.3441**
Boat (512x512)	10	28.1278	32.1973	32.4387	32.4754	32.6597	**33.5443**
	15	24.6364	30.2249	30.2710	30.2947	30.4663	**31.2868**
	20	22.1247	28.4101	28.8722	28.8994	28.9925	**29.8028**
	25	20.1715	26.7963	27.8366	27.8711	27.9429	**28.5920**
	30	18.5729	25.3963	27.0236	26.9940	27.1660	**27.7792**
Cameraman (256x256)	10	28.1449	30.5864	31.1318	31.2715	31.4361	**32.3003**
	15	24.6078	29.0860	28.6142	28.8458	29.0092	**29.7855**
	20	22.1009	27.5811	27.0871	27.1598	27.3252	**28.0848**
	25	20.1036	26.2126	25.8961	25.9618	26.0821	**26.8893**
	30	18.5796	24.9617	25.0992	25.0788	25.2519	**25.8999**

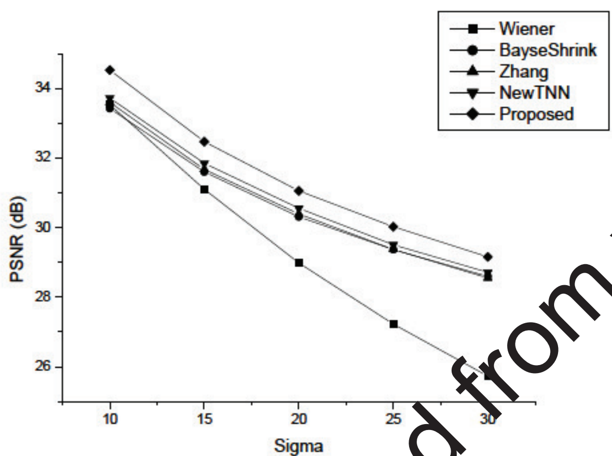

Figure 6. Comparaison of desoising performance (PSNR) for the four methods and the proposed method.

The results are compared with four methods given in literature Wiener, BayseShrink [5], Zhang [8], and New TNN [9].

By a global comparison, the experimental results (table 2 and figure 6) show better PSNR performance for the proposed method comparing to the other methods for all images test and different standard deviation.

Figures (7 and 8), show that the proposed method gives better details and edges preservation for high noise levels for all images used in simulation.

Figure 7. Image denoising results on Part of 'Lena Image' (from top to bottom): Noisy (σ=20) , Wiener2, BayseShrink [5], Zhang [8],New TNN [9],proposed method,original.

Figure 8. Some gray scale image denoising using the proposed method. From Left Noisy image (σ=30), from right proposed method.

VI. Conclusion

In this paper, we proposed a new wavelet image denoising technique using genetic algorithms and cycle spinning. The main goal for using genetic algorithms is to optimize the thresholds for each subband of DWT decomposition by using a new fitness function, On the other hand, the cycle spinning algorithm is used to reduce pseudo Gibbs phenomena and improve the denoising results.

The proposed algorithm outperforms the existing methods objectively (PSNR) and subjectively (visual quality), for all the images used is simulation and for all standard deviation of the Gaussian noise.

In future works, we will base on using SURE criteria to obtain the optimum thresholds using genetic algorithms.

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