IWSSIP 2010 - 17th International Conference on Systems, Signals and Image Processing

A New Image denoising Technique Combining the Empirical Mode Decomposition with a Wavelet Transform Technique

Faten BEN ARFIA[1], Mohamed BEN MESSAOUD[2], Mohamed ABID[1]
[1] Computer Engineering System design Laboratory (CES)
[2] Laboratory of Electronic and Information Technologies (LETI)
National Engineering School of Sfax: Tunisia.
E-mails: benarfia_faten@yahoo.fr, M.benMessaoud@enis.rnu.tn, mohamed.abid@enis.rnu.tn

Abstract—*This paper proposes a method for image denoising in the filter domain based on the characteristics of the Empirical Mode Decomposition (EMD) and the wavelet technique. The proposed method uses the EMD to the decomposition and double density wavelet to filter components. Our experimental results show that these image denoising methods are more efficient than the wavelet denoising method. Finally, the PSNR (peak signal noise ratio) and the visualization of the denoising image are used as performance comparison indexes.*

Keywords- Double Density Wavelet, Empirical Mode Decomposition, PSNR, image denoising..

I. INTRODUCTION

Generally, noise reduction is an essential part of image processing systems [1]. An image is always affected by noise in its capture, acquisition and processing. This denoising is used to improve the quality of corrupted by a lot of noise due to the undesired conditions for image acquisition. Generally, the image quality is measured by the peak signal-to-noise ratio (PSNR) or signal-to noise ratio (SNR) [2]. Traditionally, this is achieved by linear processing such as Wiener filtering. A variety of methods has emerged recently on signal denoising using nonlinear techniques in the case of additive Gaussian noise [3].

Wavelet technique is the important method of denoising in Image Processing [4]. They make it possible to analyze and identify discontinuities of a signal to one or two dimensions and on different scales. This feature is used for denoising field. However, a limitation of the wavelet approach is the need to predefine the basic functions necessary for the decomposition of the signal. Recently, Huang introduced the EMD method decomposition into sub-bands, local and self-adapting for analyzing non-stationary signals [5].

In this contribution, we combine the Wavelet and EMD techniques to denoising images as a new approach. This contribution uses the EMD as a method of decomposition and the wavelet as method of image denoising.

This paper is organized as follows: In Sec.2 we describe the new approach: the Empirical Mode Decomposition (EMD) based in wavelet technique. Sec.3 presents the evaluation criterion. In Sec.4, the experimental results of this proposed method are presented. Finally, concluding remarks are given in Sec.5.

II. EMPIRICAL MODE DECOMPOSITION BASED IN WAVELET TECHNIQUE

This is a new filtering method realized in three steps to reduce the noise in images. An edge detector is used primarily to detect the directions of the image edges. Then, the decomposition is performed by an Empirical Modal Decomposition approach [6]. The resulting images were smoothed along the four directions (each image is smoothed in contour direction): horizontal, vertical and diagonals (right and left). Finally, the image is reconstructed as it from different direction; i.e. the image pixel smoothed along the horizontal direction is used to reconstruct the same direction image, and so on. If a contour is not detected, then the average of the smoothed images in the four directions is used to reconstruct the image. Note that the choice of pixels used is based on the direction of the founded contour.

A. Detector contours in the EMD

An image contour is defined as the sudden change of intensity of the scene. In our case, we propose a methodology for detecting edges in the different orientations using the vicinity of a pixel P (i, j) (Figure.1).

	j-2	j-1	j	j+1	j+2
i+2		$a_{i+2,j-1}$		$a_{i+2,j+1}$	
i+1	$a_{i+1,j-2}$	$a_{i+1,j-1}$	$a_{i+1,j}$	$a_{i+1,j+1}$	$a_{i+1,j+2}$
i		$a_{i,j-1}$	$a_{i,j}$	$a_{i,j+1}$	
i-1	$a_{i-1,j-2}$	$a_{i-1,j-1}$	$a_{i-1,j}$	$a_{i-1,j+1}$	$a_{i-1,j+2}$
i-2		$a_{i-2,j-1}$		$a_{i-2,j+1}$	

Figure 1. The pixels of the contour directions.

The edges and their directions are calculated with the following equations:

- ✓ The vertical direction

$$A_{0k} = (a_{i-1,j-1+k} + a_{i,j-1+k} + a_{i+1,j-1+k}\ j)/3 \quad (1)$$

k=0,1,2

We calculate

$$V = \max\{|A_{0,1} - A_{0,0}|, |A_{0,1} - A_{0,2}|\} \quad (2)$$

- ✓ The horizontal direction

$$A_{1,k} = (a_{i-1+k,j-1} + a_{i-1+k,j} + a_{i-1+k,j+1})/3 \quad (3)$$

k=0,1,2

Then we calculate the contour horizontal pixel value H:

$$H = \max\{|A_{1,0} - A_{1,1}|, |A_{1,0} - A_{1,2}|\} \quad (4)$$

- ✓ The left diagonal direction

$$A_{2,0} = (a_{i-1,j+1} + a_{i,j} + a_{i+1,j-1})/3 \quad (5)$$

$$A_{2,1} = (a_{i-2,j+1} + a_{i-1,j} + a_{i,j-1} + a_{i+1,j-2})/4 \quad (6)$$

$$A_{2,2} = (a_{i-1,j+2} + a_{i,j+1} + a_{i+1,j} + a_{i+2,j-1})/4 \quad (7)$$

We calculate also

$$LD = \max\{|A_{1,0} - A_{1,1}|, |A_{1,0} - A_{1,2}|\} \quad (8)$$

- ✓ The right diagonal direction

$$A_{3,0} = (a_{i-1,j-1} + a_{i,j} + a_{i+1,j+1})/3 \quad (9)$$

$$A_{3,1} = (a_{i-1,j-2} + a_{i,j-1} + a_{i+1,j} + a_{i+2,j+1})/4 \quad (10)$$

$$A_{3,2} = (a_{i-1,j-1} + a_{i-1,j} + a_{i,j+1} + a_{i+1,j+2})/4 \quad (11)$$

Finally we calculate

$$RD = \max\{|A_{3,0} - A_{3,1}|, |A_{3,0} - A_{3,2}|\} \quad (12)$$

This calculation gives the smoothed images in all contour directions and the reconstruction of the filtered image (F) is as follows:

$$F = \max\{V, H, LD, RD\} \quad (13)$$

B. Image Smoothing

Empirical Modal Decomposition method is applied for the image smoothing [7]. This method involves the adaptive decomposition of given signal, x(t), into a series of oscillating components, IMFs, by means of a decomposition process called sifting algorithm described as follow:

1. Identify all extrema of x (t).

2. Interpolate the local maxima to form an upper envelope u(x).

3. Interpolate the local minima to form a lower envelope l(x).

4. Calculate the mean of the envelope:

m (t) = [u(x) +l(x)]/2

5. Extract the mean from the signal: h (t)=x(t)-m(t)

6. Check whether h(t) satisfies the IMF condition:

YES: h (t) is an IMF, stop sifting.

NO: let x (t) =h (t), keep sifting.

For the one-dimensional signal EMD, We can get:

$$x(t) = \sum_{i=1}^{N} h^i(t) + r(t) \quad (14)$$

Where:

N is the number of modes oscillating. $h^i(t)$ are the modes (IMF) where the first mode $h^1(t)$ component is the low level and the nth mode $h^n(t)$ is the component scale.

$r(t)$ is the residue, characterized by the non-oscillating mode.

We use the method of smoothing of unidirectional data to each of the different images: horizontal, vertical, right and left diagonal. Thus, each pixel of the four images is considered smoothed.

Each pixel of the reconstructed image is obtained by taking the highest value among the pixels of the smoothed images.

C. Wavelet transform

As shown in [8], the methodology of the discrete wavelet transform based image denoising follows three steps summarized below:

(1) Transform the noisy image into orthogonal domain by 2D discrete wavelet transform.

(2) Apply hard or soft thresholding to the noisy detail coefficients of the wavelet transform.

(3) Perform inverse discrete wavelet transform to obtain the denoised image.

Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such denoising process [9], [10].

The new version of DWT, known as Double Density DWT (DDDWT) is recently developed in [11] and [12]. It has the following important additional proprieties:

(1) It employs one scaling function and two distinct wavelets which are designed to be offset from one another by one half.

(2) The double density DWT is over complete by a factor of two.

(3) It is nearly shift- invariant where complex wavelets with real and imaginary parts approximating Hilbert pairs are proposed for denoising signal.

III. Evaluation Criteria

The proposed method is evaluated using the quality measure Peak Signal to Noise Ratio [2] which is calculated using the formula:

$$\text{PSNR (db)} = 10\log 10\{255^2/\text{MSE}\} \tag{15}$$

Where MSE is the mean squared error between the original image U and the denoised image F calculated in Equation (16).

$$MSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left|U[m,n]-F[m,n]\right|^2 \tag{16}$$

These criteria are used to evaluate the new approach and compare it with traditional methods.

IV. Experiments and Results

In our contribution we applied the EMD approach with the DWT technique for images denoising. The proposed image denoising algorithm EMD based on Double Density DWT (EMD-DDDWT) has been applied on several natural grayscale images (512×512) that are contaminated by additive Gaussian noise with different noise levels σ = 5, 10, 15, 20 and 25. Table 1 illustrates the denoising results of Lena and fruit images.

The image decomposition is performed by the EMD technique. The directions are considered to smoothing. The Double-Density DWT is used to filter the images.

To evaluate the performance of the proposed method, the comparison with the Double-Density DWT and with EMD without DWT is performed. All the denoising results are shown in Table 1, which shows that the EMD based in double density DWT technique for different noise variance provides the excellent denoising performance for the tested images.

TABLE I. PSNR (dB) Result for different denoising methods

σ	image	DDDWT	EMD	*EMD-DDDWT*
5	Lena	44,28	22,91	***45,51***
	Fruit	43,84	22,31	***45,27***
10	Lena	44,40	19,81	***45,57***
	Fruit	43,73	19,41	***44,93***
15	Lena	44,28	17,27	***45,26***
	Fruit	43,84	16,97	***44,49***
20	Lena	43,99	15,24	***44,90***
	Fruit	43,87	15,00	***44,00***
25	Lena	44,40	13,51	***44,45***
	Fruit	43,74	13,38	***43,73***

The performance of denoising method (indexed by the PSNR) is confirmed by the visual quality as shown in Figure (2).

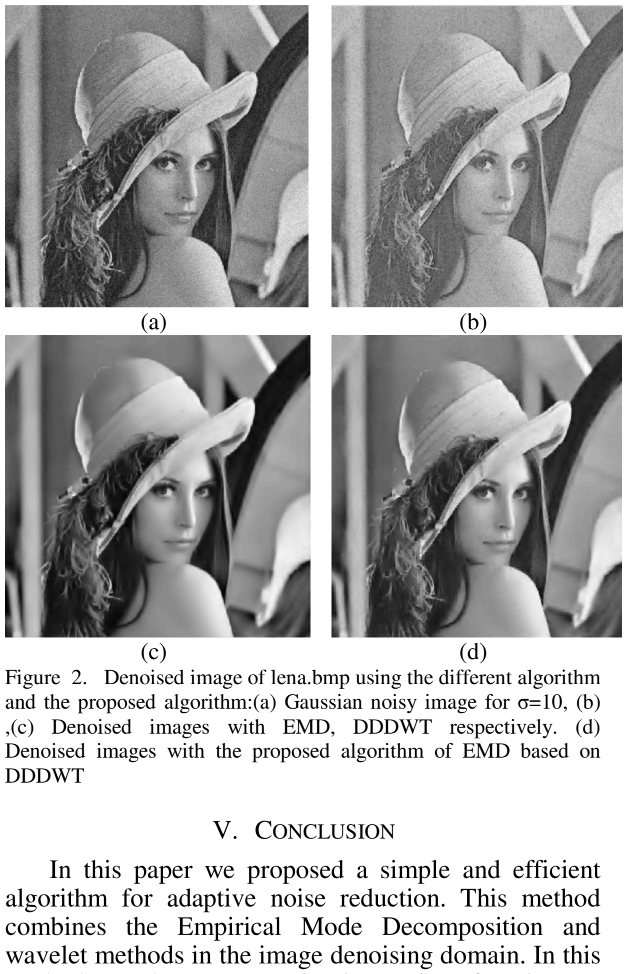

Figure 2. Denoised image of lena.bmp using the different algorithm and the proposed algorithm:(a) Gaussian noisy image for σ=10, (b) ,(c) Denoised images with EMD, DDDWT respectively. (d) Denoised images with the proposed algorithm of EMD based on DDDWT

V. Conclusion

In this paper we proposed a simple and efficient algorithm for adaptive noise reduction. This method combines the Empirical Mode Decomposition and wavelet methods in the image denoising domain. In this method, we decompose noisy image into four images smoothness following the contours of different shapes. The experiments were conducted to study the performance of the new approach in different noise levels of noisy images. The experimental results show that the proposed denoising algorithm exhibits much better performance than DDDWT and EMD in both PSNR and visual effect.

REFERENCES

[1] M.C. Motwani, M.C. Gadiya and R.C. Motwani, "Survey of Image Denoising Techniques", Proceedings of GSPx, Santa Clara, CA., Sep., 2004.

[2] C. Saravanan, R.Ponalagusamy "Gaussian Noise Estimation Technique for Gray Scale Images Using Mean Value". Journal of Theoretical and Applied Information Technology.2005 – 2007

[3] H. V. Nejad , H. R. Pourreza , H. Ebrahimi "A Novel Fuzzy Technique for Image Noise Reduction" World Academy of Science, Engineering and Technology 21 2006

[4] P. Kenterlis, D. Salonikidis, "Evaluation of wavelet domain methods for image denoising", 1st International Scientific Conference eRA, Supported by TEI of Piraeus (GR) & University of Paisley (UK), Tripolis 16-17 September 2006.

[5] N.E. Huang, Z. Shen, S.R. Long, M.L.Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C.Tung and H.H.Liu, "The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis", Proc. Roy.Soc. London A, Vol. 454, pp.903–995, (1998)

[6] P. Flandrin, P. Goncalves, "On empirical mode decomposition and its application", Ecole Normale Supérieure de Lyon 46, France.(2004)

[7] A. O. Boudraa and J. C. Cexus, "Denoising via empirical mode decomposition" in ISCCSP2006, 2006.

[8] S.K. Mohideen, S.A. Perumal and M.M. Sathik "Image Denoising using Discrete Wavelet transform". IJCSNS International Journal of Computer Science and Network Security, VOL.8 No.1, January 2008.

[10] I. Elyasi, S. Zarmehi "Elimination Noise by Adaptive Wavelet Threshold", World Academy of Science, Engineering and Technology 56 2009

[9] D.L.Donoho "De-Noising by soft-thresholding," *IEEE Trans. on Inf. Theory*, vol. 41, 3, pp. 613-627,1995.

[11] I.W. Selesnick "The double-density dual-tree discrete wavelet transforms". IEEE Trans. on Signal proc, 2001

[12] I.W.Selesnick. "The Double Density Discrete Wavelet Transform." In A. Petrosian and F. G. Meyer, editors, Wavelets in Signal and Image Analysis: From Theory to Practice. Kluwer,2001.