THE BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION WITH 2D-DWT FOR GAUSSIAN IMAGE DENOISING

Faten Ben Arfia[1], Abdelouahed Sabri[3], 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
[3]Laboratory of Electronics Signals, Systems and Computers
Faculty of Sciences, Dhar El mahraz FES. Morocco.
abdelouahed.sabri@gmail.com

ABSTRACT

This paper presents a new adaptive approach for image denoising with Gaussian noise based on a combination of the Bidimensional Empirical Mode Decomposition (BEMD) and the the discrete wavelet transforms (DWT). The BEMD is an auto-adaptive method for the analysis of nonlinear or non-stationary signals and images. The input image is decomposed into several modes called Intrinsic Mode Functions (IMFs), which show new characteristics of the images.

In this paper, we propose to apply the BEMD approach in the image denoising domain by using the first IMF to reduce the Gaussian noise in blurred images. After that, we combine the BEMD with the DWT to improve the BEMD denoising method. Finally, we show the influence of the number of IMFs filtered with the DWT on the visual quality in term of PSNR of the denoised image.

Index Terms**—** BEMD, IMF, DWT, Gaussian noise, PSNR

1. INTRODUCTION

Today, digital imaging is constantly growing in many applications, for example, object recognition, satellite imaging, biomedical, Internet, etc.

The image quality degrades due to the contamination of several types of noise. This noise corrupts the image during acquisition, transmission and storage [1].

So, the noise reduction is an important technology in image analysis and the first most important step to take before the images are processed [2].

The Bidimentional Empirical Mode Decomposition (BEMD) has developed as new approaches to processing filtering and denoising images. Better quality of results is performed than existing decomposition methods, such as Fourier Transform and Wavelets Transform techniques. The BEMD is particularly suitable for image processing such as texture analysis, image filtering and denoising. It is a nonlinear and self-adaptive filter and it is an efficient method compared to the other approach based on wavelet decomposition [3] or Gabor Transforms [4].

The BEMD decomposes an image into multiple hierarchical components called a Bidimensional Intrinsic Mode Functions (BIMFs) and a residue, this decomposition is based on the local spatial variations or scales of the image [5].

This paper presents the BEMD approach based in DWT technique for image denoising and its comparison with the most used methods in the denoising domain as the median filter, DWT transform technique and the traditional method BEMD based on histogram one.

This paper shows the influence of number of IMFs filtered on the visual quality of denoised image in term of Peak Signal to Noise ratio (PSNR) and Mean Squared Error (MSE).

This paper is organized as follows. The next section presents outlines the most significant of the Bidimensional Empirical Mode Decomposition (BEMD) and the details implementation of sifting process. We describe the proposed noise reduction approach based in the BEMD combining with the DWT technique in the section 3. The section 4 shows the experimental results and the comparison with the method used in this application. Finally, conclusions are made in Section 5.

978-1-4577-0274-7/11/$26.00 ©2011 IEEE DSP2011

2. BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION

EMD is an adaptive decomposition of signals [7], introduced by Huang [6] for one dimensional data and then extended to Bidimensional signal [8].

This novel approach is a highly adaptive decomposition. It is based on the characterization of the image with this decomposition in intrinsic mode function (IMF) where the image can be decomposed into a redundant set of signals called IMF and a residue, adding all the IMF's together with the residue reconstructs the original image without distortion or loss of information. An IMF is characterized by two specific properties [9]:

• The number of zero crossing and the number of extremas points is equal or differs only by one.

• It has a zero local mean.

The algorithm is described as follows [10]:

1. Initialization: r_0=A_0 (the residual) and k =1 (index number of IMF)
2. Extraction of the k^{th} IMF : $I_k(m,n)$
   a. Initialization:$E_0(m,n)=r_{k-1}(m,n)$ and j=1
   b. Extract the local extremas of $E_{j-1}(m,n)$ (minima and maximum)
   c. Interpolate the local extremas to construct the upper and the lower envelope respectively $Envmin_{j-1}$ (m, n) and $Envmax_{j-1}$(m, n)
   d. Calculate the average of the two envelopes:
   $$m_{j-1}(m,n) = Envmin_{j-1}(m,n) + Envmax_{j-1}(m,n)/2$$
   e. Update :
   $$E_j(m,n) = E_{j-1}(m,n) - m_{j-1}(m,n)$$
   f. Calculate the stopping criterion
   $$SD(j) = \frac{1}{N}\sum_{t=0}^{T}\left[\frac{(E_{j-1}(m,n) - E_j(m,n))^2}{E^2{}_{j-1}(m,n) + \xi}\right]$$

Where ξ is a term (low) to eliminate possible division by zero.

   g. Decision: Repeat steps (b) to (f) until $SD_i \leq SD_{max}$, and then put $I_k(m,n)$=Ej(m,n)
3. Update residual
   $$r_k(m,n) = r_{k-1}(m,n) - I_k(m,n)$$
4. Repeat steps 1-3 with j = j +1 until the number of extremas in r_j is less than 2.

The sum of all modes, added to the residual component reconstructs the original image [11]:

$$A(m,n) = \sum_{k=1}^{K} I_k(m,n) + r(m,n), k \in N^*$$

3. BEMD BASED IN BIDIMENTIONAL WAVELET TRANSFORM TECHNIQUE

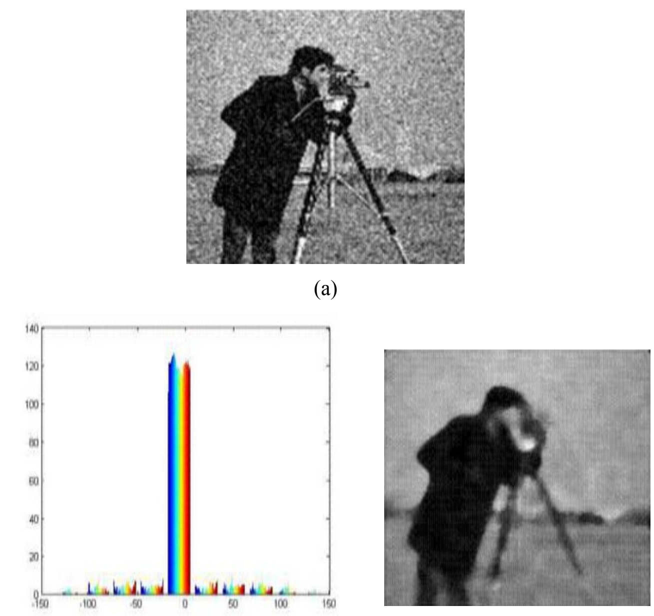
For a Gaussian noisy image, BEMD approach is very effective for decomposition and denoising images, but during decomposition can be see that the first IMF and probably the second can contains the largest amount of noise.

The wavelet transform is applied to filter the first and second IMF to improve the visual quality of the denoised image in term of the PSNR criterion.

Several research projects have used the BEMD as filtering approach but it does not give good results in terms of visual quality. In this approach, they assumed that the noise is low amplitude that the extremas points. Therefore, the first IMF contains almost all the noise. So, to reduce the noise in a noisy image, they just reject all values lower than a specified threshold in the extremas points of the first IMF. They leave only the extremas points which are considered of significant points [12].

This threshold is determined from the histogram method of minimum and maximum extremas [13].

The proposed method is easy to implement but it causes a loss of information and poor visual quality in the denoised image as shown in Figure 1.



(a)

(b)

(c)

Fig. 1. BEMD for denoising image: a) noisy image, b) histogram of the first IMF extremas, c) denoised image with BEMD

Our approach consists in using the Wavelet Transform for filtering the first and the second IMF because the first IMF does not contain the amount of noise. In fact, this noise can also exist in the second IMF. This approach can improve visual quality and better performances than the traditional methods of image denoising. The description of the proposed approach is illustrated in the figure 2.

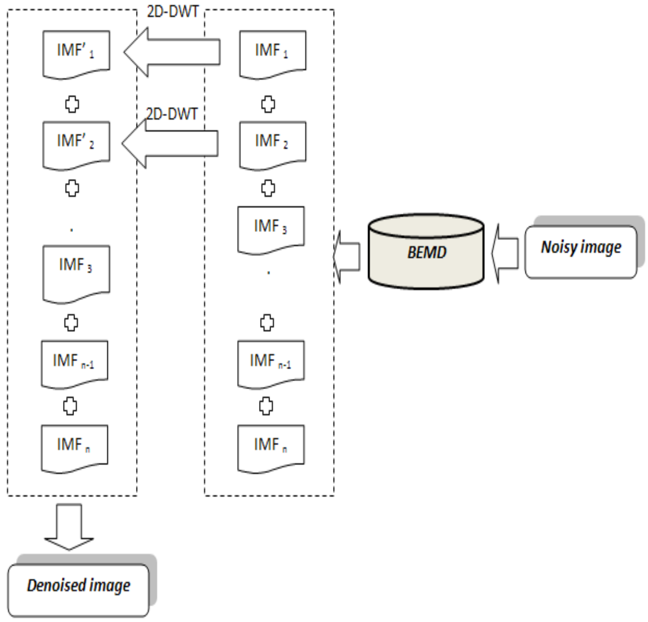


Fig. 2. Denoising image approach based in BEMD combined with DWT.

4. EXPERIMENTS AND RESULTS

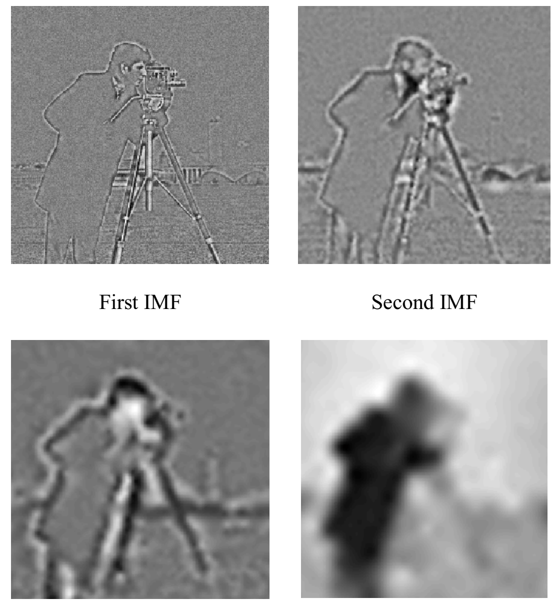
In our contribution we applied the BEMD approach with the DWT technique for image denoising. The proposed image approach has been applied on several natural grayscale images (512×512) that are contaminated by additive Gaussian noise with different noise levels σ = 5, 10, 15, 20 and 30. Table 1 illustrates the denoising results of "cameramen.bmp" using BEMD with a single and 2 IMFs filtered with the discrete wavelet transforms DWT.

TABLE 1
PSNR (dB) AND MSE VALUES FOR THE IMAGE DENOISING USING BEMD WITH DWT

	BEMD (1 IMF)		BEMD (2 IMF)	
	PSNR	MSE	PSNR	MSE
5	36,55	14,38	37,70	14,16
10	31,80	41,94	32,97	39,28
15	29,07	80,54	30,30	76,03
20	27,21	123,48	28,50	119,90
30	24,49	224,95	25,90	224,90

According to the results shown in the second column of table 1, it's not sufficient to filter the first IMF to obtain a excellent result because the second IMF also can contain a quantity of noise. The filtering of this second IMF ameliorates the visual quality of the image in term of PSNR and MSE.

The figure 3 presents the decomposition of the noisy image with BEMD in 3 IMFs and a residue.



First IMF Second IMF

Third IMF Residue

Fig. 3. Noisy image decomposition with BEMD

The figure 4 shows the performance of our approach based in BEMD with DWT compared with the DWT and the median filter like methods of denoising.

In comparison with traditional methods, table 2 and figure 4 illustrate the performance of our approach based in BEMD with DWT compared with the DWT and the median filter as nonlinear methods of denoising.

TABLE 2
COMPARISON RESULTS FOR DENOISING METHODS IN TERM OF PSNR (dB)

σ	noisy	Median	DWT	BEMD (2 IMF)
5	34,1604	34,02	35,0402	37,7069
10	28,1277	29,55	30,8039	32,9732
15	24,5812	25,7856	28,4068	30,3026
20	22,0957	24,0327	26,012	28,5063
30	18,5739	20,374	23,0379	25,9099

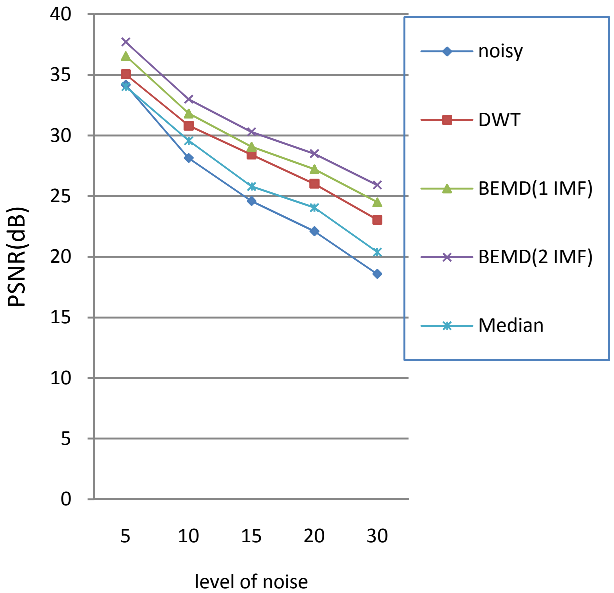
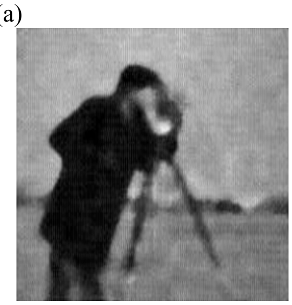


Fig. 4. PSNR performance of the proposed method compared with the DWT and the Median filter

As illustration, the proposed approach gives better results to the levels of visual quality compared with the BEMD with the histogram approach as explained in paragraph 2 (figure 5).

(a)

(b)



(c)

Fig. 5. (a) The noisy image with Gaussian noise =20, (b) denoised image with BEMD with DWT (2 IMF filtred), (c) BEMD with histogram.

5. CONCLUSION

The BEMD is adaptive image decomposition. The obtained IMFs can be seen as results of filter bank. The results of a simple use of the BEMD for image denoising prompted us to improve it to have a very powerful tool for image denoising. The idea proposed is to combine the BEMD with the 2D-DWT. Our approach consists in using the wavelet transform for filtering the first two IMFs. This is due to that the first IMF does not contain the amount of noise but this noise can also exist in the second IMF. The proposed approach has been tested on several natural grayscale images (512×512) that are contaminated by additive Gaussian noise with different noise levels = 5, 10, 15, 20 and 25. The results presented in comparison with DWT show the efficiency of our proposed approach which can improve effectively image visual quality and performs better than traditional methods of image denoising.

6. REFERENCES

[1] R. C. Gonzalez and R. E. Woods "Digital Image Processing," Second Edition, Prentice-Hall, 2002

[2] D.L. Donoho and L.M. Johnstone, "Ideal Spatial Adaptation via Wavelet Shrinkage, " Biometrika, vol.81, pp.425-455, Sep 1994.

[3] S. G. Mallat, " A theory for multiresolution signal decomposition: the wavelet representation, " IEEE Trans. Pattern Analysis and Machine Intelligence, Vol 11, No.7, pp.674-693, 1989.

[4] P. Perona and J. Malik, " Scale-space and edge detection using anisotropic diffusion, " IEEE Trans, Pattern Analysis and Machine Intelligence, Vol. 12, No. 7, pp.629-639, 1990.

[5]C. Damerval , S. Meignen and V. Perrier, " A fast algorithm for bidimensional EMD, " IEEE Signal Processing Letters, Vol. 12, No. 10, pp. 701-704, 2005.

[6] NE. Huang, Z. Shen, SR. Long, MC. Wu, HH. Shih, Q. Zheng, N-C. Yen, CC. Tung and HH. Liu, "The empirical mode decomposition and the Hilbert spectrum For non-linear and non-stationary time series analysis, " Proc R Soc Land Ser A, pp. 903-995, 1998.

[7] F.Ben Arfia, M. Ben Messaoud and M. Abid "A New Image denoising Technique Combining the Empirical Mode Decomposition with a Wavelet Transform Technique " IWSSIP 2010 - 17th International Conference on Systems, Signals and Image Processing,2010.

[8] J. C. Nunes, Y. Bouaoune, E. Delechelle, O. Niang and Ph. Bunel, " Image analysis by bidimensional empirical mode decomposition, " Image and Vision Computing, 2003.

[9] A. Linderhed, "2D empirical mode decompositions - in the spirit of image compression," Proc. of SPIE, Vol. 4738, pp.1-8, 2002.

[10]A. Sabri, M. Karoud, H. Tairi and A. Aarab, "Fast Bidimensional Empirical Mode Decomposition Based on an Adaptive Block Partitioning, " IJCSNS International Journal of Computer Science and Network Security, VOL.8, No.11, November 2008.

[11] A. Linderhed, "2D empirical mode decomposition in the spirit of image compression" , Wavelet and ICA Applications IX, SPIE Proceedings, Orlando, vol. 4736, pp. 1-8, 2002.

[12] A. Linderhed, "Image Empirical Mode Decomposition: a New Tool for Image Processing, " Advances in Adaptive Data Analysis 1(2): 265-294 ,2009.

[13] S. Abdelouahed, "Décomposition multimodale empirique bidimensionnelle : Améliorations et Applications". Thèse, university of Sidi Mohammed Ben Abdellah Faculty of sciences Dhar el Mehraz Fes, 2009.