Image decomposition based on modified Bidimensional Empirical Mode Decomposition

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ABSTRACT

In this paper we develop an adaptive algorithm for decomposition of greyscales images. This method is highly adaptive decomposition image called Bidimentional Empirical Mode Decomposition (BEMD). It is based on the characterization of the image through its decomposition in Intrinsic Mode Function (IMF) where it can be decomposed into basis functions called IMF and a residue. This method offered a good result in visual quality, unfortunately this method consume an important execution time. To overcome this problem we proposed a new approach using Block based BEMD method where the input image is subdivided into blocks. Then the BEMD is applied on each of the four blocks separately. This method offered a good solution to reduce the execution time.

Keywords: EMD, BEMD, Execution time, Wavelet, PSNR

1. INTRODUCTION

Digital images play an important role both in day to-day applications, such as, satellite television, video conference. Image decomposition as well as in areas of research and technology such as image filtering, image analyzing and medical imagery.

Among the most common multiresolution methods of image decomposition [1] include: spectral methods [2], Gabor functions [3] and wavelet transforms [4]. We present a decomposition of image based on the method of Multimodal Empirical Decomposition (EMD), introduced by Huang [5]. This approach provides a powerful tool for auto-adaptive multiscale analysis of non-stationary signals. This technique has been successfully in many scientific problems. Its main advantage that it does not depend on an a priori basis set and starts from the data itself to decompose the signals in spatial domain [6].

The BEMD approach is the two-dimensional version of the Empirical Mode Decomposition (EMD) which is based on decomposition nonlinear and non-stationary signals into intrinsic mode functions (IMFs) [7]. These functions are mono-component that has well-defined instantaneous frequencies. The BEMD has the same principle of EMD; it decomposes the input image into two-dimensional IMFs. This paper presents the modified BEMD based on the decomposition of the image blocks. This approach can solve the problem of the calculation time which has a handicap of BEMD approach for large images.

This paper is organized as follow. Section 2 presents outlines the most significant of the Bidimensional Empirical Mode Decomposition (BEMD) and the details implementation of sifting process. Section 3 describes the modified BEMD based on the decomposition of the image blocks. In section 4 the experimental results of this proposed method are presented. Finally, a conclusion is presented in Section 5.

2. THE BIMENTIONNAL EMPIRICAL MODE DECOMPOSITION

The BEMD approach is an adaptive decomposition of the images. It is based on the characterization of an image through its decomposition in intrinsic mode function (IMF) where the image can be decomposed into a redundant set of signals

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denoted IMF and a residue. Adding all the IMF's together with the residue, the original image can be reconstructed without loss or distortion information [8]. An IMF is characterized by some specific properties [9]:

- Have the same number of zero- crossings and extrema.
- The mean value of the upper and the lower envelopes is equal to zero.

The bidimensional sifting process is defined as follows [10]:

1. Initialization: A0=r (the residual) and k =1 (index number of IMF)
2. Extraction of the kth IMF : Ik(m,n)

a. Initialization:E0(m,n)=rk-1(m,n) and j=1

b. Extract the local extrema of Ej-1(m,n) (minima and maximum)

c. Interpolate the local extrema to construct the upper and the lower envelope respectively Envminj-1 (m, n) and Envmaxj-1(m, n)

d. Calculate the average of the two envelopes:

$$m_{j-1}(m,n) = \mathrm{E}nv\mathrm{min}_{\mathrm{j-1}}\,(\mathrm{m,n}) + \mathrm{E}nv\mathrm{max}_{\mathrm{j-1}}\,(\mathrm{m,n})/2 \qquad (1)$$

e. Update :

$$E_j(m,n) = E_{j-1}(m,n) - m_{j-1}(m,n) \quad \text{, avec } \mathrm{j = j+1} \qquad (2)$$

f. Calculate the stopping criterion

$$SD(j) = \frac{1}{N}\sum_{t=0}^{T}\left[\frac{(E_{j-1}(m,n) - E_j(m,n))^2}{E^2{}_{j-1}(m,n) + \xi}\right] \qquad (3)$$

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

g. Decision: Repeat steps (b) to (f) until SDi ≤ SDmax, and then put Ik(m,n)=Ej(m,n)

3. Update residual

$$r_k(m,n) = r_{k-1}(m,n) - I_k(m,n) \qquad (4)$$

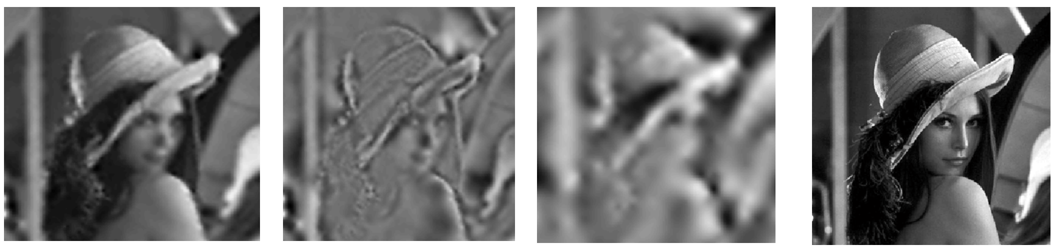
4. Repeat steps 1-3 with j = j +1until the number of extrema in r j is less than 2.

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

$$A(m,n) = \sum_{k=1}^{K} I_k(m,n) + r(m,n), k \in N^* \qquad (5)$$

The Lena image presented in figure 1(a) is decomposed by BEMD algorithm. The correspondent IMF and residues are presented in figures 1 (b, c and d) and (e, f and g) respectively and finally the reconstructed image (h).

(a)image original (b) mode 1 (c) mode 2 (d) mode 3



(e) residue 1 (f) residue 2 (g) residue 3 (h) reconstructed image

Figure 1: BEMD in three modes

3. BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION BASED IN IMAGE BLOCKS

The execution time presents a great handicap for the decomposition of large images. For solving this problem we propose a new approach based on the decomposition of original image into four blocks then the application of the BEMD algorithm of blocks separated is performed.

In the sifting process we will treat each block independently of the others for estimating the maximum and minimum two envelopes.

This has the result of applying the interpolation function RBF on small areas. As an example for an image of 512 * 512 the decomposition BEMD is treated on four separate blocks as shown in figure 4.The proposed approach BEMD based in block image offers a good solution for reduction the execution time compared with the BEMD. Unfortunately, with the important gain in execution time this approach can cause the side effect (artefact)

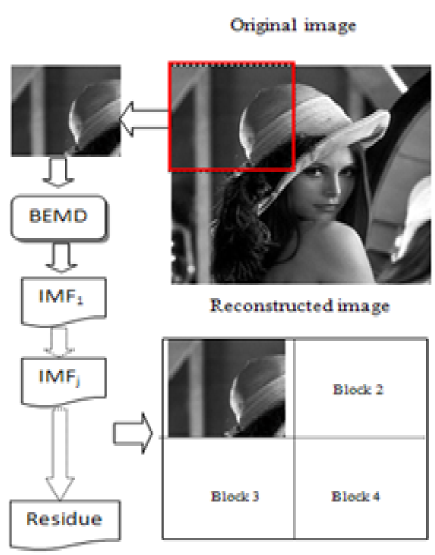


Figure 2: The blocks based BEMD

4. EXPERIMENTATION AND RESULTS

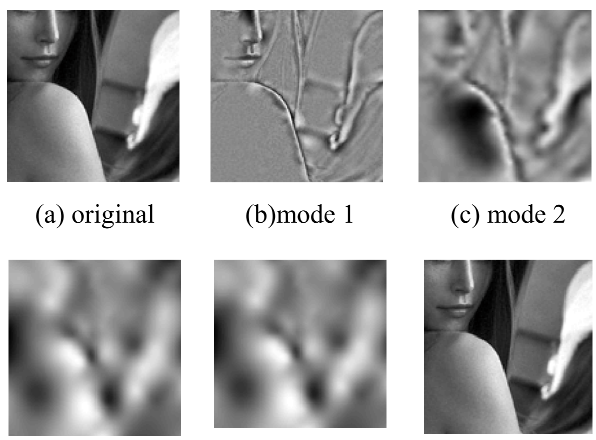
To evaluate the results we apply the BEMD on blocks of the image Lena (256 * 256) presented in Figure 3.

We aim to compare our approach BEMD with those proposed in this domain, as example the wavelets transform technique [12]. Their PSNR are depicted in Table 1.

Table 1: PSNR (dB) values for the image decomposition using BEMD and DWT

	BEMD	**DWT**
PSNR (dB)	347,69	267,132

The results presented in Table 1 shows that the PSNR value of the technique called BEMD indicates that the quality of the reconstructed image is very good compared with the wavelet transform technique.



(a) original (b)mode 1 (c) mode 2

(d) mode 3 (e) residue (f) reconstuted

Figure 3: Block based BEMD in block of image

Unfortunately, this technique consumes more in terms of execution time which presents a problem for real time applications.

In the sifting process of the BEMD based blocks we will treat each block independently for estimating the two maximum and minimum envelopes. This has the result of applying the interpolation function RBF on small areas.

The input image is subdivided into four sub-blocks as illustrated in figure 6, and then the BEMD approach is applied on each block separately. So in this modified BEMD approach, the execution time decreases as shown in Table 2. The examination of visual quality of the reconstructed image demonstrates the performance of the procedure.

Block 1	Block 2
Block 3	Block 4

Figure 4: The input image divided into blocks

Table 2: values for execution time for the image decomposition using BEMD and BEMD based Block

<table>
<tr><td rowspan="2"></td><td colspan="4">Block-based BEMD</td><td>BEMD</td></tr>
<tr><td>Bloc1</td><td>Bloc2</td><td>Bloc3</td><td>Bloc4</td><td rowspan="2"></td></tr>
<tr><td rowspan="2">Time (s)</td><td>7,066</td><td>6,191</td><td>7,971</td><td>8,99</td></tr>
<tr><td colspan="4">30,218</td><td>64,64</td></tr>
</table>

In the sifting process we will treat each block independently for estimating the two upper and lower envelopes. This has the result of applying the interpolation function RBF on small areas. This makes for this reason, it possible to reduce the execution time and solve this problem for images of large sizes.

CONCLUSION

In this paper, we presented the BEMD approach and the BEMD based on image block decomposition. The experimental results show that the BEMD is more efficient than the traditional methods such as wavelet, but it consumes excessive execution time. So the BEMD based in blocks image is proposed to reduce this parameter. This approach is very similar to the BEMD with a big reduction of the execution time.

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