A new BEMD method based on self-similar feature and its application

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Outline

1. Introduction

2D signal or image:

1) The data may be shorter.
2) The shapes and continuity of edges are very important
3) Process the larger number of elements
4) No 2D instantaneous frequency (or local wave number)

1. Introduction

Texture analysis is widely recognized as a difficult and challenging computer-vision problem. It provides many applications such as in remote sensing image and medical image diagnosis, document analysis, and target detection, etc.

Texture features are determined by the spatial relations between neighboring pixels.

Approaches:
statistical, geometrical, model based, signal processing

1. Introduction

Signal processing approches :

Gabor filters ,wavelet transforms,Wigner distributions, discrete cosine transforms or DCT.

Those approches are weak at processing nonlinear and non-stationary signals.

Bidimensional Empirical mode decomposition is used as a texture analysis tool for many reasons.

- Firstly, BEMD is a fully data-driven method and using no predetermined filter or wavelet functions. It is independently from any fixed basis function.
- Secondly, each 2D-IMF obtained by BEMD can be analyzed locally and independently in the same way through the Hilbert-Huang Transform.

1. Introduction

The main processing of the EMD is to decompose the signal to its intrinsic mode functions (IMFs), and then those IMFs are analyzed by the Hilbert transform. This process is also known as Hilbert-Huang transforms (HHT). For two-dimenational signals, there is bidimensional EMD (BEMD).

One topic of the BEMD questions is the boundary effect processing, which is to reduce the boundary effect to the intrinsic mode functions (IMFs) .

Solution:

- One way is to view the image as a long lengthened vector and then apply the one dimensional extended method to solve it .
- The other way is to extend the image by mirror extending, neural network training or AR model et.

2. Review of BEMD

Empirical Mode Decomposition

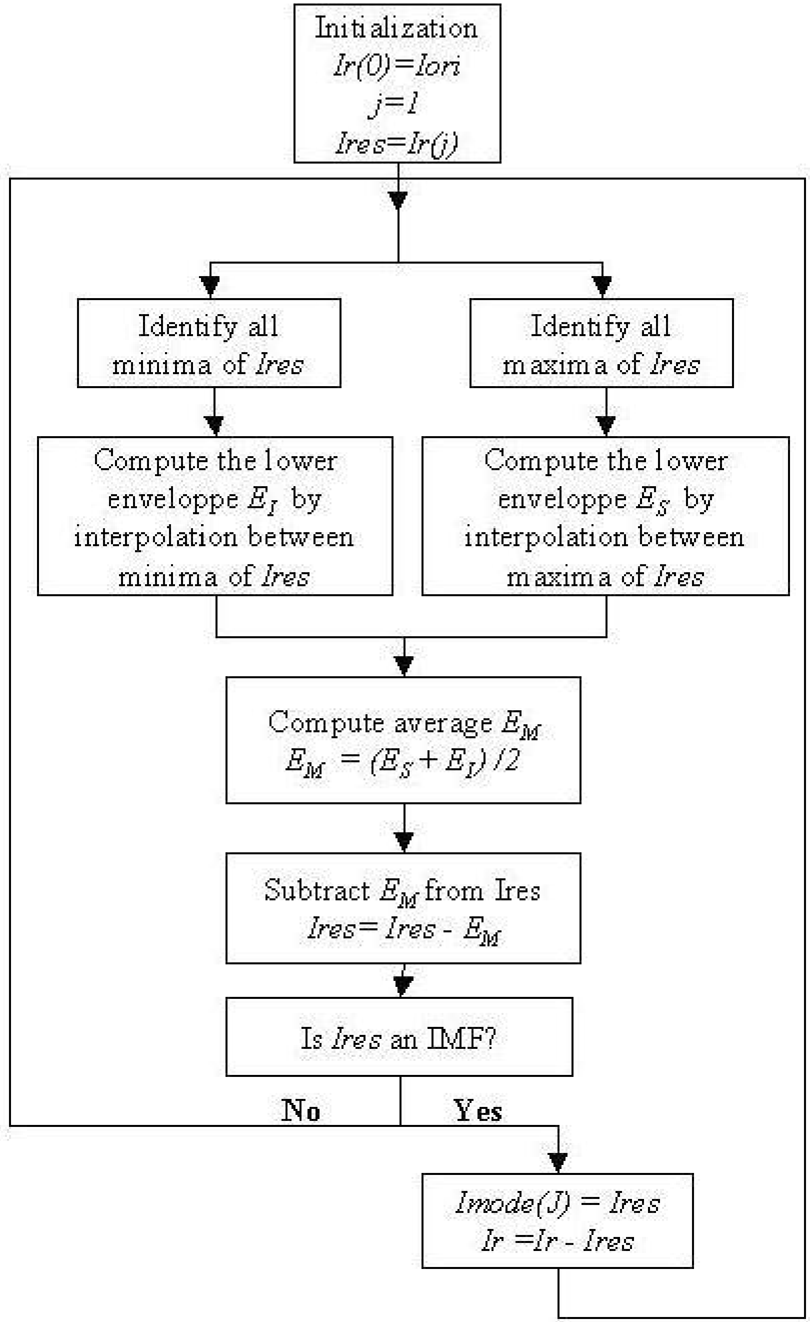
EMD decomposes signals into components called Intrinsic Mode Functions (IMFs) satisfying the following two conditions:

(a)The numbers of extrema and zero-crossings must either equal or differ at most by one;

(b)At any point, the mean value of the envelope defined by the local maxima and the envelope by the local minima is zero.

Huang [1] have also proposed an algorithm called ’sifting’ to extract IMFs from the original signal *f*(*t*) as follows:

$$f(t) = \sum_{i=1}^{N} I_i(t) + r_N(t) \qquad f_H(x) = f(x) * \frac{1}{\pi x} = \frac{1}{\pi} \int \frac{f(\tau)}{x - \tau} d_\tau$$



Initialization
Ir(0)=Iori
j=1
Ires=Ir(j)
Identify all minima of *Ires*
Identify all maxima of *Ires*
Compute the lower enveloppe E_I by interpolation between minima of *Ires*
Compute the lower enveloppe E_S by interpolation between maxima of *Ires*
Compute average E_M
$E_M = (E_S + E_I)/2$
Subtract E_M from Ires
$Ires = Ires - E_M$
Is *Ires* an IMF?
No
Yes
$Imode(J) = Ires$
$Ir = Ir - Ires$

3. The new BEMD details

3.1 Local extrema detection

Detection the local extrema means finding the local maxima and minima points from given images. BEMD[8] use mathematical morphology method to local the extrema, but we find the extrema points will be reduced fast.

Definition 1: x[i,j] is a maximum (or. minimum) if it is larger (or. lower) than the value of *f* at the nearest neighbors of *[i,j]*.

$$x_{mn} = \begin{cases} Local\ Maximum & if\ x_{mn} > x_{ij} \\ Local\ Minimum & if\ x_{mn} < x_{ij} \end{cases}$$

$$\begin{aligned} & x_{ij} = \{x \mid (m-w) : i : (m+w), (n-w) : j : (n+w)\} \\ & i \neq m,\ j \neq n \qquad (7) \end{aligned}$$

3. The new BEMD details

3.1 Local extrema detection

Detection the local extrema means finding the local maxima and minima points from given images.

8	8	4	1	5	2	6	3
6	3	2	3	7	3	9	3
7	8	3	2	1	4	3	7
4	1	2	4	3	5	7	8
6	4	2	1	2	5	3	4
1	3	7	9	9	8	7	8
9	2	6	7	6	8	7	7
8	2	1	9	7	9	1	1

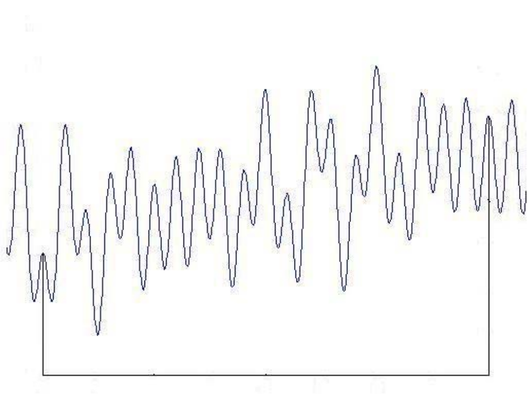
0	0	0	0	0	0	0	0
0	0	0	0	7	0	9	0
0	8	0	0	0	0	0	0
0	0	0	4	0	0	0	8
6	0	0	0	0	0	0	0
0	0	0	0	0	0	0	8
9	0	0	0	0	0	0	0
0	0	0	9	0	9	0	0

0	0	0	1	0	2	0	0
0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0
0	1	0	0	0	0	0	0
0	0	0	1	0	0	3	0
1	0	0	0	0	0	0	0
0	0	0	0	6	0	0	0
0	0	1	0	0	0	0	0

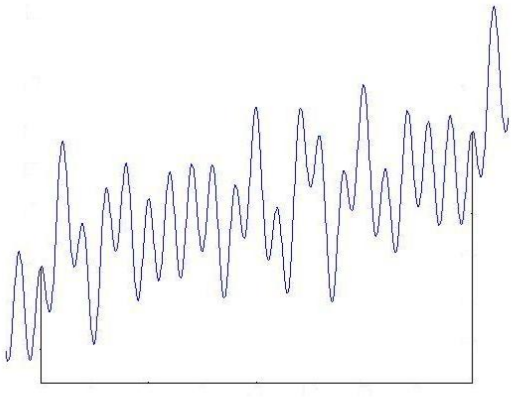
3. The new BEMD details

3.2 Self-similar for BEMD Boundary Processing

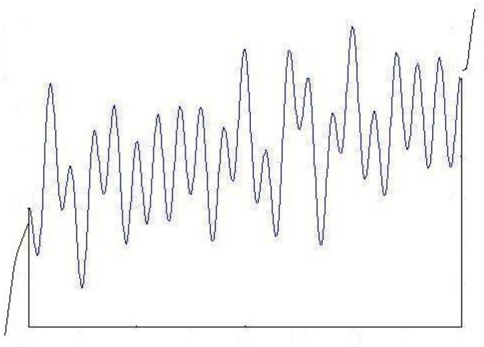
Boundary processing is a main topic in the BEMD approaches.



mirror method



circle method



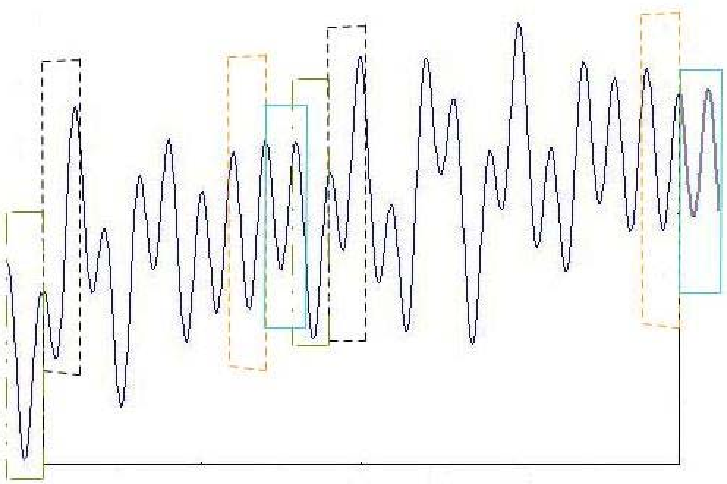
fitting method

3. The new BEMD details

3.2 Self-similar for BEMD Boundary Processing

A self-similar object is exactly or approximately similar to a part of itself, which means the whole has the same shape as one or more of the parts. Parts of them show the same statistical properties at many scales.

W use this self-similar property to build the extend boundary. The basic idea is: the extend part can find a self-similar part in the original signal.



3. The new BEMD details

3.2 Self-similar for BEMD Boundary Processing

self-similar

3. The new BEMD details

3.3 Surface interpolation method

Another difficulty in the BEMD comes from generating a smooth fitting surface to the identified maxima and minima.

Solution :

radial basis function (RBF)

spline surface interpretation

Delaunay triangulation

Delaunay triangulation can effectively reduce the interpolation computation. Our interpolation method is based on a Delaunay triangulation.

4. Image denoising based on the new BEMD

The EMD has found a vast number of diverse applications such as biomedical, watermarking, and audio processing. A more generalized task in which EMD can prove useful is image denoiseing. [12]

The energy of the IMFs of a noise-only signal with certain characteristics is known, then in actual cases of signals comprising both information and noise following the specific characteristics, a significant discrepancy between the energy of a noise-only IMF and the corresponding noisy-signal IMF indicates the presence of useful information.

In ref[12, IEEE SP 2009], a thresholding principle based method is used in the decomposition modes resulting from applying EMD to a signal.

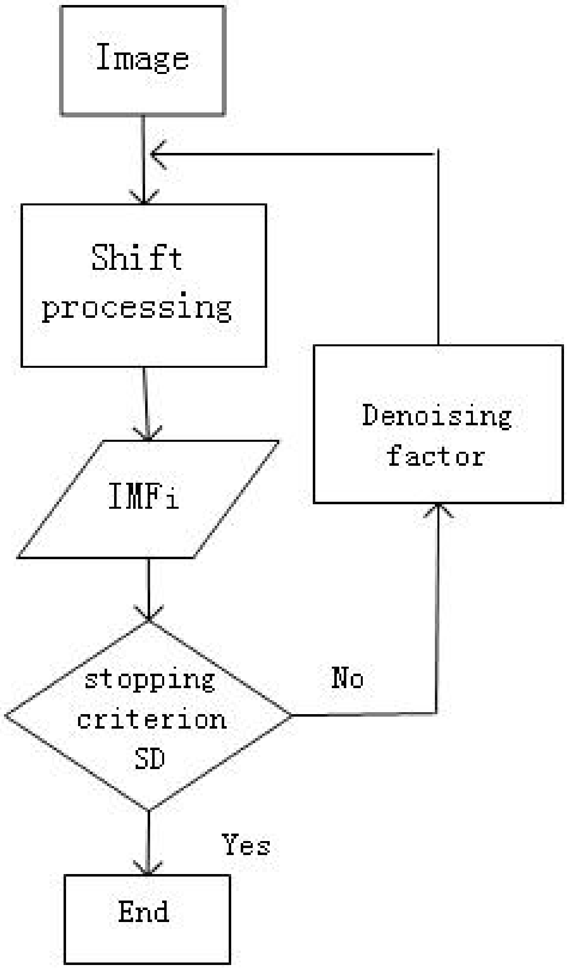
4. Image denoising based on the new BEMD

In this part, we proposed an image denoising method based on the new BEMD. First, the noised image is decomposed by the BEMD, and then, the IMFs are denoised by the denoising factor by different parameters, at last, the denoised compon ents are composed.

Denoising factor:

$$F(x,y)=\begin{cases} w(x,y) & \left|w(x,y)\geq 2\sigma\right| \\ 0 & \left|w(x,y)\leq \left|aver\right|\right| \\ w(x,y)\times k & else \end{cases}$$

4. Image denoising based on the new BEMD



5. Experimental results

5.1 the new BEMD decomposition result

(a) Original image

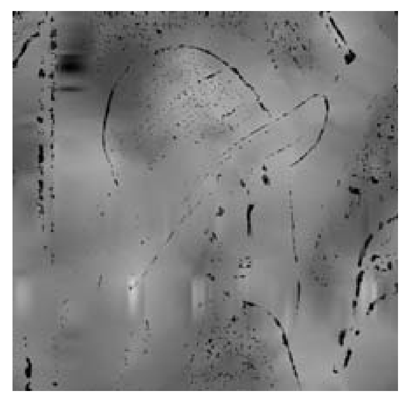
(b) IMF1

(c) IMF2

(d) IMF3

(d) IMF4

(e) IMF5



(f) IMF6

(h) Residue

5. Experimental results

5.1 the new BEMD decomposition result

The orthogonaltiy index (OI), has been proposed for IMFs, which is used to measure the IMFs' decomposition result. A low value of the OI indicated a good decomposition in terms of local orthogonality among the IMFs [4,7].

Methods	OI	Consuming time (s)
Nunes[8]	0.0033	68.52
Linderhed [9]	0.0029	60.51
Our method	0.0025	46.59

Table 1. Compared result of Orhogonaltiy index (OI) and the consuming time

5. Experimental results

5.2 The new-BEMD based image denoising result

(a) noise image (PSNR: 18.718)

(b) median filter

(c) Wiener filter

(d) Nunes[8]+ factor

(e) Our approach

5. Experimental results

5.2 The new-BEMD based image denoising result

Output PSNR / Input PSNR	Median filter	Wiener filter	Nunes[8] + factor	New BEMD + factor
18.718	24.323	24.59	26.287	29.31
16.146	22.947	22.61	24.599	27.307
14.508	21.66	21.352	24.402	26.503

Table 2 denoising result with output PSNR

The result shown that based on the BEMD and denoise factor, the noise can be reduced more effetely than the traditional methods. And the new BEMD's denoise result is also better than the Nunes' BEMD.

6. Conclusion and future work

- Aimining for the boundary effects of BEMD, a new BEMD method is proposed, which is based on the self-similar feature and the neighbor local extremes.

- Based on the new BEMD method, we proposed an image denoising method, compare with the normal denoising algorithm, the BEMD-based method can achieve a good result.

- BEMD has present as a locally adaptive method and suitable for the analysis of nonlinear or nonstationary signals. Its AM-FM analysis characteristic provides a new texture analysis tool to do many processing.

- As a new theory, there are many works to improve the BEMD, such as the theoretical foundation for EMD, the boundary processing, the surface interpolation approaches. In the future, we will focus on developing a better BEMD method and more research about the BEMD application in image processing and pattern recognition.

Selected References

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THANK YOU VERY MUCH