An Improved Block Stitching Method based on Bidimensional Empirical Mode Decomposition

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Keywords: blocked Bieimensional Empirical Mode Decomposition(BEMD) ,symmetry similarity variance, blocking artifact, self-adaption splicing,radial basis function.

Abstract. The bidimensional empirical mode decomposition based on block partitioning(BBEMD) by using of radial basis function interpolation reduces the computational cost, but the blocking artefact is noticeable in the resulting mode. For alleviating the blocking artefact problem, we proposed a modified BBEMD. We calculate the enlargement size of each image block by the minimal symmetry resemblance variance of adjacent blocks, and integrate the decomposing results through a self-adaptive seamless splicing method.The experimental results demonstrate the effectiveness of the proposed method in alleviating the blocking artefact.

1 Introduction

Analysis of nonlinear and non-stationary data is always a problem for the signal processing field. In 1998, US scientists Huang and his team proposed a creative Empirical Mode Decomposition (EMD) algorithm and intrinsic mode function (imf)[1]. Compared to the Fourier analysis based on priori basis functions and wavelet analysis, EMD is more suitable for handling non-linear, non-stationary signals as it is a multi-scale analysis method that relies on data-driven[2]. The one-dimensional EMD has been used in many fields like mechanical engineering, geophysics, fault monitoring. In 2003, Nunes put forward a two-dimensional EMD (BEMD) algorithm[3], which pushed the development of EMD a step forward. Currently, the top three ways of BEMD algorithm used by most researchers are: BEMD based on radial basis function interpolation(Recorded as BEMD)[3], BEMD based on triangulation interpolation(Recorded as BEMD-2)[4], and Direction EMD(Recorded as DEMD)[5]. Each has its advantages and disadvantages. BEMD has a better interpretation in different layers, but calculates slower[6,7].In order to solve the problem of BEMD's computing speed, Karoud proposed BEMD algorithm[8], which greatly improved its speed, but led to uncontinuous distortion of image and big error; BEMD advanced by Sabri reduced the error[9]. This paper presents a BEMD algorithm based on block-image symmetry similarity variance and self-adaptive seamless splicing. Experiments shown that the proposed method can stitch different IMF without distortion while ensure the calculating speed.

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2 Algorithm description

Assume that $I_1(x,y)$ and $I_2(x,y)$ are two adjacent image blocks. The dimension is $m \times n$. If I_1 and I_2 are two horizontal adjacent image blocks (see Fig.1 (a)), then the horizontal symmetric similarity variance between $I_1(x,y)$ and $I_2(x,y)$ -- D_h^i can be defined as:

$$E_h^0 = e_h^0 = 0,$$

$$e_h^i = \sum_{k=1}^{m} (I_1(k, n+(i-1)) - I_2(k,i))^2,$$

$$E_h^i = E_h^{i-1} + e_h^i,$$

$$D_h^i = \frac{1}{i} \times E_h^i, i = 1,2,\cdots$$

If I_1 and I_2 are two vertical adjacent image blocks (see Fig.1 (b)), then the vertical symmetric similarity variance between $I_1(x,y)$ and $I_2(x,y)$ -- D_v^i can be defined as:

$$E_v^0 = e_v^0 = 0,$$

$$e_v^i = \sum_{l=1}^{n} (I_1(m-(i-1),l)) - I_2(i,l))^2,$$

$$E_v^i = E_v^{i-1} + e_v^i,\ D_v^i = \frac{1}{i} \times E_h^i,\ i = 1,2,\cdots$$

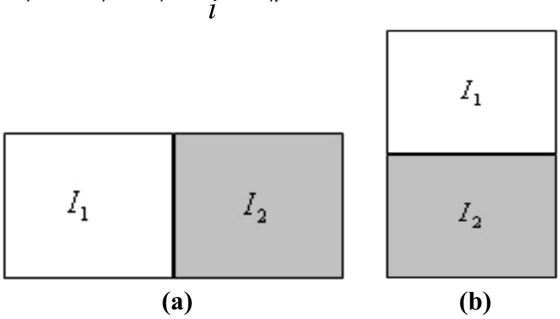

Figure 1. The location of two adjacent image block.

Now the minimal symmetry similarity variance of the two images (i.e. The maximal symmetrical similar area is the overlapping area) can be calculated.
This is the algorithm of I_1 and I_2 's continuation size:

(1) If $i = 1$, calculate D_h^1 (or D_v^1);

(2) If $i = i+1$, calculate D_h^i (or D_v^1);

(3) If $D_h^i \le D_h^{i-1}$ (or $D_v^i \le D_v^{i-1}$), then repeat step 2-3; if not, go to step 4.

(4) If $i_h = \max(i-1, \frac{m}{16})$ (or $i_v = \max(i-1, \frac{n}{16})$),

then i_h is I_1 's horizontal continuation size in the right direction, I_2 's horizontal continuation size in the left direction. i_v is I_1 's vertical continuation size on down side, and I_2 's vertical continuation size on the upper side.

After the image is decomposed by overlapping block of BEMD algorithm, if we splice the imf in different layers directly, there will be significant discontinuity distortion in the all layers except imf1. Here is the idea of using natural stitching algorithm to realize the uniform transition of adjacent blocks: the overlapping area of the left and right images must be composed into a new image according to certain weighted value, the composed formula is: $f_{new} = f_{left} \times (1-d) + f_{right} \times d$, in which f_{new} is the composite image of the overlapping area, f_{left} and f_{right} are the overlapping part of left and right image respectively; d is a gradient factor, if the width of the overlapping area is W, then with the transition of the composite image from left to the right, d ranges in $[0,1]$. The same way goes for the composition of the up and down images.

In the experiment we found that imf2 get a better improvement with the use of natural stitching algorithm, but distortion still remains in imf3 and subsequent imfs, especially for the ghosting and blurring in the overlapping area. This is because there is a big difference of pixel gray between the overlapping areas of the two images, leaving a jump in the gray value of the composite image. To avoid this, we should analyze the features of results of blocked BEMD algorithm:

The adjacent block I_1 and I_2 overlap sections are set as shown in Fig. 2. According to the screening method of BEMD, it can be concluded that after decomposition of I_1, the error of L_{11} is smaller than that of the not decomposed one. As for L_{12}, due to the influence of the boundary effects, the error is bigger. Similarly, in I_2, the error of L_{22} is smaller than L_{21}, which is closer to the results of the unblocked. Therefore, for the overlapping area on the left (L_{11} and L_{21}), assume that $f_{right}(i,j)$ is the corresponding point of L_{11} in a certain pixel point $f_{left}(i,j)$, if the value difference between $f_{left}(i,j)$ and $f_{right}(i,j)$ is bigger, then $f_{left}(i,j)$ is closer to the real value, while the error of $f_{right}(i,j)$ is bigger. Therefore, at this time we can take $f_{left}(i,j)$ as of the value of f_{new} directly. If the value difference between $f_{left}(i,j)$ and $f_{right}(i,j)$ is smaller, then we take their weighted average value as f_{new} in order to reduce the error. Similarly, for the right part we can adopt the same method.

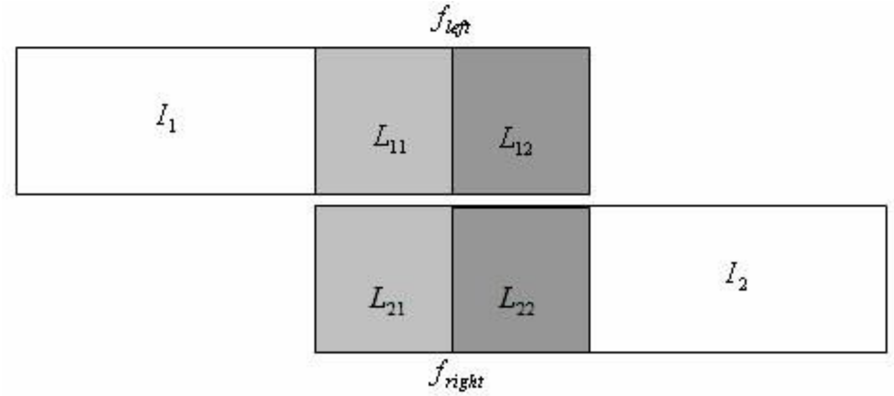

Figure 2. Two adjacent overlapping image block diagram.

To find out the difference between $f_{left}(i,j)$ and $f_{right}(i,j)$, we need to introduce a threshold value-door. The author defines the average value of error sum of squares of f_{left} and f_{right} in 9 neighborhood as the threshold value. That is:

$$door = \frac{\sum_{x=-1}^{1}\sum_{y=-1}^{1} | f_{left}(i+x, j+y) - f_{right}(i+x, j+y) |^2}{9}.$$

Then in the modified synthesis algorithm, the synthetic image is :

$$f_{new}(i,j) = \begin{cases} f_{left}(i,j), \ | f_{left}(i,j) - f_{right}(i,j) | \geq door, (i,j) \in L_{11} \\ f_{left}(i,j) \times (1-d) + f_{right}(i,j) \times d, | f_{left}(i,j) - f_{right}(i,j) | < door, (i,j) \in L_{11} \cup L_{12} \\ f_{right}(i,j), \ | f_{left}(i,j) - f_{right}(i,j) | \geq door, (i,j) \in L_{12} \end{cases}$$

The self-adaptive BEMD algorithm can roughly be divided into the following steps:

(1) Divide the image into small 4^k pieces, $k = 1, 2, \cdots$;

(2) Calculate the size of the overlapped portion of each mini-block in accordance with image expansion algorithm;

(3) Decompose each extended mini-block by BEMD;

(4) Stitch the imf of all layers and the remainder through an adaptive algorithm.

3 Experiments and analysis

Divide an image of a Woman (256×256) into four mini-blocks. Firstly, calculate extension size of the each mini-block in accordance with the symmetry variance stated . The calculated horizontal and vertical extension dimensions are: $i_h = 22$, $i_v = 17$,respectively. Decompose the four mini-blocks by BEMD, here take $SD = 0.1$. Synthesize the Imf and the remainder of the layers, then compare with the results of Block BEMD (BBEMD)[8] and overLapped Block BEMD(LBBEMD)[8]. The Imf and the remainders of all layers are shown in Fig.3.

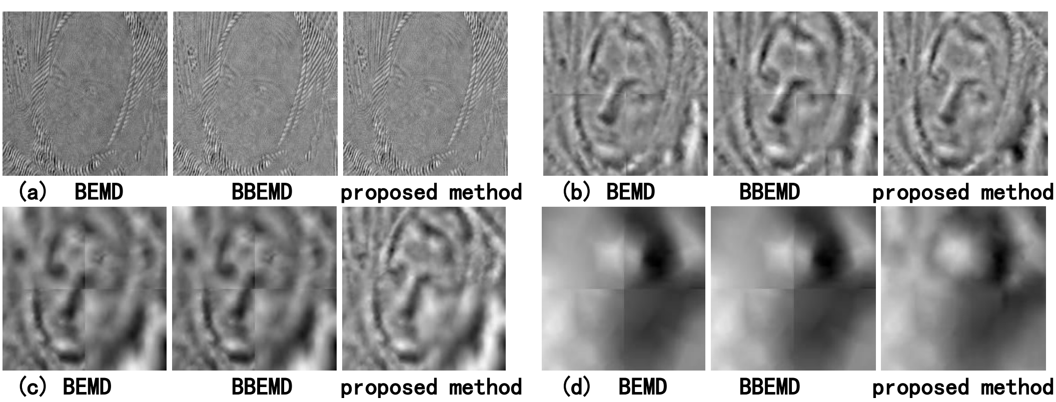

Figure 3. Decomposing imfs of Woman, Fig.3(a)—(d) representing imf1, imf2, imf3 and res

From the visual effects, it can be seen from Fig.3 that the imf1 of the three methods has no obvious patchwork. But for imf2, imf3 and the remainders, there are obvious patchwork, and stitching error is quite big. The results obtained by the author's method is better, without obvious patchwork.

Taking BEMD decomposition results of the unblock image as a standard, compare the Mean Square Error(MSE) and Peak Signal to Noise Ratio(PSNR) of different decomposition methods[10]. The results are shown in Table 1. From Table 1, we can see that compared with other methods, the author's method have some improvement in all imf layers. Compared with LBBEMD method, the MSE of the Woman image in imf1, imf2, imf3 and res reduced respectively: 1.03, 12.96, 21.90, 43.24, with an average reduction of 19.78. PSNR increased respectively: 0.48, 1.16, 1.01, 0.99, with an average of 0.91.

All the experiments of this paper are carried out in Matlab environment and under the same conditions. It takes 20.4298s to directly BEMD decompose the Woman image. But this method takes 15.5724s. We can see that this method can better improve the quality of the results as well as guarantee computing speed.

Table 1. (a) Each Imf's MSE of Woman

	BBEMD	LBBEMD	proposed method
imf1	11.9723	9.8588	8.8320
Imf2	68.2394	55.2126	42.2489
Imf3	94.1556	107.1826	85.2837
Imf4	134.1515	133.5685	90.3247

Table 1. (b) Each imf's MSE of Woman

	BBEMD	LBBEMD	proposed method
imf1	37.3490	38.1926	38.6702
Imf2	29.7907	30.7104	31.8726
Imf3	28.3923	27.8296	28.8211
Imf4	27.1913	27.5872	28.5727

4 Conclusion

The BEMD algorithm based on radial basis function interpolation has a better interpolation and fitting, but a slower calculation speed. Block BEMD algorithm can effectively reduce the computation time, but after there is discontinuous distortion in splices of synthesis imf and remainders of all layers. This paper presents an algorithm based on block-image symmetry similarity variance and self-adaptive seamless splicing. Experiments shown that this method can stitch different imf without distortion while ensure the calculating speed.

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