A NEW MULTI-FOCUS IMAGE FUSION BASED ON TWO-DIMENSIONAL EMD AND GENETIC ALGORITHM

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ABSTRACT

A multi-focus image fusion method based on two-dimensional empirical mode decomposition and genetic algorithm is presented in this paper. First, a two-dimensional empirical mode decomposition is applied to the decomposition of source images. High and low frequency of intrinsic mode function component are classified by a T-test. Then low frequency coefficients are fused by improved maximum regional information entropy criterion whereas the high frequency coefficients are amalgamated in different threshold ranges of coefficients by regional correlation. The regional correlation threshold is selected by search of genetic algorithm. Finally, combined results are obtained by inverse two-dimensional empirical mode decomposition transform on fusion coefficients. Simulation results show that the proposed algorithm significantly outperforms traditional image fusion methods that are based on the pixel, region, and wavelet, respectively.

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I. INTRODUCTION

Most of image fusion methods are based on normal or higher level of wavelet algorithm. Although these methods can decompose image well and obtain good fusion results, the selection of wavelet basis function [1] is always a difficult problem. Moreover, image fusion of local features for each pixel or small region leads to the loss of strong local correlation characteristics. Nevertheless, two dimensional EMD (empirical mode decomposition) algorithm [2, 3], which has adaptive features, can multi-scale decompose image signals according to its characteristics. The produced adaptive basis functions are processed and analysed by Hilbert transform on each level. The algorithm obtains high and low frequency with similar component level and strong correlation. High frequency displays shape feature and contour of image and low frequency shows whole information of image.

Research [4-6] of multi-focus image fusion algorithm based on two-dimensional EMD mainly concentrated on the fusion rules of IMF (intrinsic mode function) component, among which image fusion based on regions has achieved promising results [6]. However, determination of region matching threshold was usually determined by experience [7]. Nevertheless, genetic algorithm is a random search and optimization method which imitates natural selection and genetic mechanism of biological world to solve the complex problems. It has advantages of high efficiency, parallelism and global optimization in evolution process. Consequently, the multi-focus image fusion method based on two-dimensional EMD and genetic algorithm is presented in this paper.

II. TWO-DIMENSIONAL EMD

Decomposition process of two-dimensional EMD [4] is as follows.

1. External initialization. Two-dimensional \( M \times N \) image signal is \( f(x, y), x=1, \ldots, M, \ y=1, \ldots, N \). Image defined as \( r_j(x, y) = f(x, y) \) is processed.

2. Screening and extracting IMF, \( j=1 \).
   i. \( h_j(x, y) = r_{j-1}(x, y) \).
   ii. Maximum and minimum value of \( h_{j-1} (k=1) \) are calculated by 8 pixel neighborhood or morphology.
   iii. \( u_{\text{max}}(x, y) \) and \( u_{\text{min}}(x, y) \) were received by envelope fitting on minimum and maximum value points. Thereinto, \( u_{\text{max}}(x, y) \) and \( u_{\text{min}}(x, y) \) respectively represent the minimal and maximal envelope surface value of 2D image.

3. Calculation formula of residual quantity:
   \[ r_j(x, y) = h_{j-1}(x, y) - m(x, y) \]

4. Result of two-dimensional EMD decomposition is as follows.
   \[ f(x, y) = \sum_{j=1}^{n} c_j(x, y) + r_n(x, y) \]

Among which: \( f(x, y) \) is synthetic signal, \( c_j(x, y) \) is obtained IMF component of the \( j \) decomposition, \( n \) is decomposition number of IMF component, \( r_n(x, y) \) is Residue (the final residual component). Fig. 1 shows process of algorithm as follows.

Decomposition of two-dimensional EMD, which brings IMF mode component, is a process from smallest to largest decomposition on scale. Edge detail information of image is extracted, and then smoothing region is gradually selected. Decomposition of two-dimensional EMD, which only needs to set stop criteria and boundary conditions without setting a basis function, can carry out scale decomposition of images from small to large conveniently and easily. As shown in Fig. 2, a sample image decomposed by two-dimensional EMD [5] brings 4 IMFs and 1 Residue.
As is showed in Fig. 2, smallest scale component presents in first IMF, and smaller scale component exists in the second IMF. In turn, curve information of different scales can be extracted furthest by selection. Procedure obtained components is similar to decomposition through a narrow-band filter. So each component, which has very strong correlation between the inner pixels, is processed as an entirety in image fusion.

III. IMAGE FUSION BASED ON TWO-DIMENSIONAL EMD AND GENETIC ALGORITHM

1. Image fusion based on two-dimensional EMD

Firstly, image sources A and B, which have been image registration, are decomposed by two-dimensional EMD. Then a T test is made to check whether the zero on mean of IMF coefficients. Part of larger test value is used as high frequency and the smaller is put as low frequency. Two-dimensional EMD components \( \{IMF^A_{j,H}, IMF^B_{j,H}\} \) and \( \{IMF^A_{j,L}, IMF^B_{j,L}\} \) are obtained respectively. Thereinto, \( j \) is decomposed scale, \( L \) represents the low frequency information of image, \( H \) is high frequency information of image. Resulting coefficients are processed by fusion rules. Finally, fused image is received from inverse two-dimensional EMD. Fig. 3 is flow of image fusion algorithm based on two-dimensional EMD.

Image fusion rule, which is key point of image fusion, directly influences quality of fused image by optimal degree of image processing. Low and high frequency information decomposed by two-dimensional EMD has a distinct physical meaning. Therefore, detail information of high frequency and approximate information of low frequency for image should be distinguished using different fusion operators and fusion rules in image fusion processing.

i. Fusion rule of low frequency coefficients

Low frequency image information retains image profile information. Fusion strategy based on region not only persists a large number of information of original image and adjacent neighborhood information, but also enhances relevance of pixels in image region. In addition, due to presence of significant correlation among image
pixels which is seen as an amplitude characteristic, image fusion effect can be effectively improved by increase of center pixel amplitude information in area. Therefore, an improved weighted regional maximum information entropy criterion is used as the fusion rule of low frequency coefficients.

\[
E^L_j(x, y) = \text{Entropy}\left(\sum_{m=-1}^{1} \sum_{n=-1}^{1} W(m, n) \text{IMF}^L_{j,m,n}(x + m, y + n)\right) \tag{4}
\]

\[
E^B_j(x, y) = \text{Entropy}\left(\sum_{m=-1}^{1} \sum_{n=-1}^{1} W(m, n) \text{IMF}^B_{j,m,n}(x + m, y + n)\right) \tag{5}
\]

\[
W = \frac{1}{12} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 4 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{6}
\]

\[
\text{IMF}^L_{j,m,n}(x, y) = \text{IMF}^L_{j,m,n}(x, y) \quad E^L_j(x, y) \geq E^B_j(x, y)
\]

\[
\text{IMF}^B_{j,m,n}(x, y) = \text{IMF}^B_{j,m,n}(x, y) \quad E^L_j(x, y) < E^B_j(x, y)
\]  \tag{7}

Thereinto, \( \text{IMF}^L_{j,m,n} \), \( \text{IMF}^A_{j,m,n} \) and \( \text{IMF}^B_{j,m,n} \) represent respectively low frequency coefficients of fused image and source images (A and B) in scales \( j \). \( E^L_j \) and \( E^B_j \) are regional information entropy of source images A and B in scale \( j \). \( \text{Entropy}() \) indicates calculation information entropy of variables in brackets.

**ii. Fusion rule of high frequency coefficients**

Spatial frequency reflects change trend of gray in window. Larger spatial frequency corresponds to some mutations, such as edges, texture and other important information in image. Spatial frequency detects details of image features in high frequency information. So adaptive fusion rule based on region, which selects space frequency as metric and combines with adaptive factor, is used for high frequency component. Spatial frequency reflects overall activity level of an image in spatial domain. Spatial frequency definition of image is shown below.

\[
SF = \sqrt{RF^2 + CF^2} \tag{8}
\]

\( RF \) is line frequency of image and \( CF \) is train frequency of image in the formula, definitions are respectively as follows.

\[
RF = \frac{1}{9} \sum_{m=-1}^{1} \sum_{n=-1}^{1} \left[ \text{IMF}^L_{j,m,n}(x + m, y + n) - \text{IMF}^B_{j,m,n}(x + m, y + n - 1) \right]^2 \tag{9}
\]

\[
CF = \frac{1}{9} \sum_{m=-1}^{1} \sum_{n=-1}^{1} \left[ \text{IMF}^L_{j,m,n}(x + m, y + n) - \text{IMF}^B_{j,m,n}(x + m - 1, y + n) \right]^2 \tag{10}
\]

Correlation coefficient is used to distinguish interdependency of corresponding high frequency with neighborhood window in two images.

\[
\text{Corr}(\text{IMF}_{H,j,m,n}^{L,w}, \text{IMF}_{H,j,m,n}^{B,w}) = \frac{\sum_{m=-1}^{1} \sum_{n=-1}^{1} \left[ \text{IMF}^L_{H,j,m,n}(x + m, y + n) - \text{IMF}^L_{H,j,m,n}(x + m, y + n) \right] \left[ \text{IMF}^B_{H,j,m,n}(x + m, y + n) - \text{IMF}^B_{H,j,m,n}(x + m, y + n) \right]}{\sqrt{\sum_{m=-1}^{1} \sum_{n=-1}^{1} \left[ \text{IMF}^L_{H,j,m,n}(x + m, y + n) - \text{IMF}^L_{H,j,m,n}(x + m, y + n) \right]^2} \times \sqrt{\sum_{m=-1}^{1} \sum_{n=-1}^{1} \left[ \text{IMF}^B_{H,j,m,n}(x + m, y + n) - \text{IMF}^B_{H,j,m,n}(x + m, y + n) \right]^2}} \tag{11}
\]

\( \text{IMF}_{H,j,m,n}^{L,w} \) and \( \text{IMF}_{H,j,m,n}^{B,w} \) severally represent \( 3 \times 3 \) window area of high frequency subbands information in two images. Region size of \( w \) is \( 3 \times 3 \). Threshold \( \delta \) is set. When \( \text{Corr}(\text{IMF}_{H,j,m,n}^{L,w}, \text{IMF}_{H,j,m,n}^{B,w}) < \delta \), it presents low correlation of two region. Larger spatial frequency means stronger mutation of high frequency information in images, so region contains more features. Area of larger spatial frequency (SF) in two region is used as high frequency information of fused image.

If \( \text{Corr}(\text{IMF}_{H,j,m,n}^{L,w}, \text{IMF}_{H,j,m,n}^{B,w}) \geq \delta \), correlation of two regions is large. So characteristic included in two images is similar. Weighted coefficients determined by spatial frequency of region are as follow.
So high frequency information of image fusion is below.

\[
\begin{align*}
IMF_{w}(x,y) &= \begin{cases} 
    w_{max} \times \text{IMF}^{v}_{i}(x,y) + w_{min} \times \text{IMF}^{s}_{i}(x,y) & \text{IF}(\text{IMF}^{v}_{i}) > SF(\text{IMF}^{s}_{i}) \\
    w_{max} \times \text{IMF}^{v}_{i}(x,y) + w_{min} \times \text{IMF}^{s}_{i}(x,y) & \text{IF}(\text{IMF}^{v}_{i}) \leq SF(\text{IMF}^{s}_{i})
\end{cases}
\end{align*}
\]

(14)

Selection of correlation threshold value \( \delta \) is generally between 0.5-0.8 [8], in which, optimal value depends on images to be fused. Genetic algorithm is used to search optimal threshold value in this paper.

2. Determination of correlation threshold by genetic algorithm

As a key point, Determination of correlation threshold is an improvement for previous algorithm in this paper. GA (Genetic Algorithm) is a non numerical optimization method, which borrows genetic point of view and utilizes "survival of the fittest" mechanism to obtain optimum solution of problem. Algorithm process is shown in Fig. 4.

Core of genetic algorithm is to determine fitness function. Fitness function, which is determined by objective function based on problem to be solved, is a standard using to distinguish stand or fall of individual in groups. So fitness function is not only driving force of evolution process in algorithm, but also only basis of natural selection. Taking information entropy of fused image as objective function can maximize information of fused image, thus, more information of texture and detail can be extracted. When threshold \( \delta \) is \( \beta \), fused image is \( F_{\beta} \)

\[
\text{Fitness}(\beta) = \text{entropy}(F_{\beta})
\]

(15)

Specific implementation steps are as follows: the first step is to generate initial population. First, coding scheme should be determined. Real coding is adopted in this paper. As widely validated opinion [8], real coding is most effective for function optimization problem. Then, initial population is generated. According to correlation threshold between 0.5 and 0.8, population \( \{\beta_1, \beta_2, \ldots, \beta_N\} \) can be randomly generated uniformly distributed in this range. Choosing optimization process is to select \( \beta_i \), for maximizing information entropy of fused image.

The second step is to determine genetic operator. Genetic operators include selection, crossover and mutation operator. As a process of copy, selection can choose high fitness individuals from population. Probability of an individual being selected is as follow.

\[
P(\beta_i) = \frac{\text{Fitness}(\beta_i)}{\sum_{i=1}^{N} \text{Fitness}(\beta_i)}
\]

(16)

Crossover operation is main way to generate new individuals by recombination. Before Crossover operation, selected \( N_s \) individuals are paired into \( N_s/2 \) groups like individuals of \( N_s/2 \). According to formula (15), intermediate recombination of real valued coding is applied in this paper.

\[
\beta_i = \beta_i + \omega (\beta_j - \beta_i)
\]

(17)

\( \omega \) is conversion coefficient generating uniformly from an interval.

Role of mutation operator is to disrupt original gene value and randomly generate new value within scope. Mutation operations are used according to the following way.

\[
\beta_i = \beta_i + \lambda
\]

(18)

Received variation value \( \beta_i \) is produced by addition of original value \( \beta \) and mutation step \( \lambda \) randomly generating from range [-1, 1].

IV. EXPERIMENTAL RESULT AND ANALYSIS

Two pieces of grayscale image and color image [11]
in different focus are taken from www.imgfsr.com. Fusion experiments of images compare fusion effect of different methods. Pixel fusion, regional fusion based on two-dimensional EMD (the fusion rules are low frequency using weighted average and high frequency using maximum rules) and wavelet method with 2 layer decomposition in reference [11] are compared with the proposed method in this paper. Regional correlation threshold of image fusion based on two-dimensional EMD is set to 0.65 in proposed method. Regional correlation threshold is searched by genetic algorithm. Thereinto, the largest genetic algebra is 20 and mutation probability is 0.01. Region size of two methods is $3 \times 3$.

1. Gray image fusion Results

Gray images are image sources in this section. As is shown in Fig. 5(a), source image A is a left focal image. A right focal source image B is shown in Fig. 5(b). From comparison among Fig. 5(d), 5(e), 5(f) and 5(g), fusion result using pixel fusion rule appears low definition and obvious defocusing region; image adopting regional fusion rule [12] presents clear edge stitching and regional spectrum distortion; image fusion results with wavelet [11] shows a lower contrast. Improved algorithm in this paper not only avoids shortcomings of pixel fusion [10], regional fusion [12] and wavelet fusion, but also appears uncertain spectrum distortion in lighter areas and obvious edge preserving advantage. So image obtained by the proposed method has greater increase in contrast and clarity. Fig. 5(c) is ideal image.

2. Color image fusion results

Pixel fusion, regional fusion, wavelet fusion rule [11] and the proposed method are applied on each image channel in experiments. As shown in Fig. 6(a), left focal image is source image A. Fig. 6(b) is right focal image source B. Fig. 6(d), 6(e), 6(f) and 6(g) are the fused images separately using pixel fusion, region fusion, wavelet fusion rule and the proposed method in this paper. Fig. 6(c) is ideal image. More obviously seen from the chart, fusion image using the proposed method has strong increase on contrast and clarity than other three methods [13, 14].

3. Analysis of evaluation index

Objective evaluation indexes [15] such as IE (information entropy), CC (correlation coefficient), RMSE (root mean square error) and PSNR (peak signal to noise ratio) are applied on multi-focus image fusion in Experiments, contrastive results are in Table 1. The bigger of IE presents better fusion results and more information in fused image; close to 1 of CC shows that fused image is more similar to ideal image; Smaller RMSE indicates that better fusion quality and fusion effect of fused image and more adjacency between fusion image and ideal image; Higher PSNR also illustrates good fusion quality and fusion effect.

As shown from IE in Table 1, the proposed method, which
Table 1  Comparison of evaluation results based on fusion methods

<table>
<thead>
<tr>
<th>Image Algorithms</th>
<th>Evaluating Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IE</td>
</tr>
<tr>
<td>Pixel fusion</td>
<td>7.0301</td>
</tr>
<tr>
<td>Regional fusion</td>
<td>7.2768</td>
</tr>
<tr>
<td>Wavelet fusion</td>
<td>7.4025</td>
</tr>
<tr>
<td>Proposed method</td>
<td>7.4782</td>
</tr>
</tbody>
</table>

Fig. 6  Experimental results of multi-focus color image fusion

is compared with pixel fusion, region fusion and wavelet fusion rules, is improved in extent of rich image information. Other evaluating indexes such as CC, RMSE and PSNR objectively show advantages of the proposed method, this is basically same as visual analysis above.

V. SUMMARY

Two dimensional EMD, which is an image analysis tool with strong local feature relevant characteristics, appears ascendency in image fusion field. Therefore, a multi-focus image fusion algorithm based on the combination of two-dimensional EMD and genetic algorithm has been proposed in this paper. The proposed algorithm not only effectively overcame blind selection of correlation threshold based on regional fusion, but also avoided edge anamorphose and spectral distortions phenomenon in traditional image fusion algorithm. Experimental results have shown that the proposed algorithm can more effectively elevate contrast and sharpness in image fusion than other three state-of-the-art algorithms.

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