A medical image fusion method based on energy classification of BEMD components

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A medical image fusion method based on bi-dimensional empirical mode decomposition (BEMD) and dual-channel PCNN is proposed in this paper. The multi-modality medical images are decomposed into intrinsic mode function (IMF) components and a residue component. IMF components are divided into high-frequency and low-frequency components based on the component energy. Fusion coefficients are achieved by the following fusion rule: high frequency components and the residue component are superimposed to get more textures; low frequency components contain more details of the source image which are input into dual-channel PCNN to select fusion coefficients, the fused medical image is achieved by inverse transformation of BEMD. BEMD is a self-adaptive tool for analyzing nonlinear and non-stationary data; it doesn’t need to predefine filter or basis function. Dual-channel PCNN reduces the computational complexity and has a good ability in selecting fusion coefficients. A combined application of BEMD and dual-channel PCNN can extract the details of the image information more effectively. The experimental result shows the proposed algorithm gets better fusion result and has more advantages comparing with traditional fusion algorithms.

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1. Introduction

Medical image fusion is a hot spot in medical image processing domain. At present, medical imaging mode is divided into two categories: anatomical imaging modality and functional imaging modality. All medical image information is combined to process the fusion of the multi-modality image, it benefits for finding more valuable information.

Medical image fusion aims at SPECT and MRI, CT and MRI, SPECT and CT etc., multimode medical images. Wavelet transform is widely used in medical image fusion. It has good frequency characteristics, but the wavelet transform depends on the predefined filter or the wavelet basis function; on the other hand, different filter or wavelet basis function has a great influence in fusion results.

In order to expand the multi-scale analysis method, Huang proposed intrinsic mode function (IMF) and empirical mode decomposition (EMD) in 1998 [1]. EMD is an adaptive and multi-scale signal processing tool. The method can analyze non-linearity and non-stationary data well [2]. EMD is a novel data representation and it has better spatial and frequency characteristics than wavelet analysis. 1D EMD with better physical characteristics can be expanded to analyze 2D signal. EMD has already been used in the field of physical geography, biomedicine, mechanical engineering and other fields [3].

In the process of 1D EMD screening, cubic spline function that constructs enveloping surfaces will be divergent in both ends of the data series and the edges will have large errors. On the other hand, the errors propagate inward in the process of screening and data series are polluted. Data will have boundary effect after Hilbert transformation.

For high-frequency IMF components are influenced by the boundary effect of EMD less than low-frequency IMF components [4], in order to improve the result of medical image fusion, dual-channel PCNN is proposed to select low-frequency coefficients in this paper. IMF components on each layer include different spatial scale information. Although textures in several spatial scales are different obviously, the method is convenient to extract these textures.

The outline of the paper is as follows. We introduce the BEMD in Section 2 to state method of BEMD in images decomposition and BIMF component classifier. In Section 3, we introduce dual-channel PCNN which is good at selecting fusion coefficients. In Section 4, the proposed fusion method is used for selecting coefficients which are from BEMD. Then, we introduce the fusion steps in details. In Section 5, we detailed analyze the advantages of the algorithm proposed in the paper using several groups of experiments and comparing with classical methods of medical image fusion. In Section 6, it is conclusions.
2. BEMD and BIMF component classifier

2.1. Method of BEMD

For 2D signal, such as image, source image can be decomposed into several 2D IMF components and a residue component by BEMD [5,6], whose frequencies are from high to low. BIMF meets two constraints: the local mean of the original 2D signals should be symmetric and its own mean is zero; its maximum is positive, minimum is negative. IMF components have the following characteristics: (1) In data set, the number of maximum points set and minimum points are equal to the number of zero crossing points, or their difference is less than 1; (2) At any point, the mean of envelope constituted by minimum and maximum is close to zero. IMF components are near orthogonal, they represent every frequency of local data and they correspond to high-frequency and low frequency data, the residue component represents development tendency of the original image. BEMD is a kind of completely self-adaptive decomposition, a large extent image decomposition depends on the characteristics of data itself. It means that if screening stop condition is consistent, the number of IMF depends on the data characteristics [7]. So, the number of BIMF may be different in different images. The steps of BEMD algorithm are as follows:

1) Initialization, the residue component \( R = I \), \( I \) is the source image.
2) If the residue \( R \) is monotone or it reaches decomposition number of an image, the algorithm stops; Otherwise, make \( H = R \) and the screening process starts.
3) The extrema in image \( P \) are achieved, maximum points set and minimum points set in the region are searched.
4) The maximum points set and the minimum points set are plane interpolated, and upper enveloping surfaces \( U(m, n) \) and lower enveloping surfaces \( L(m, n) \) of the image are achieved, the mean value \( M \) of the image \( H \) is also solved by enveloping surfaces.

\[
M(m, n) = (U(m, n) + L(m, n))/2
\]

5) \( H_k(m, n) = H_{k-1}(m, n) - M(m, n) \), screening process is used for judging the stop condition which is shown in formula (6), if the stop condition is not satisfied, turns to step 3.
6) If the BIMF \( D(m, n) = H(m, n) \), an IMF component is achieved.
7) Function \( R(m, n) \) can be expressed by \( R(m, n) = R(m, n) - D(m, n) \), and turns to step 2.

In the above method, the cores of the method are plane interpolation, how to get extrema and screening stop condition. After \( J \) layers BEMD, the final decomposition process can be expressed as:

\[
l(m, n) = \sum_{j=1}^{J} D_j(m, n) + R_j(m, n), j \in N
\]

where \( D_j \) is the \( j \)th 2D BIMF, \( R_j \) is the residue component after \( J \) layers decomposition.

2.2. Time-frequency characteristics of BEMD

1D IMF is a kind of simple-component, at any time, there is only an instantaneous frequency, and its instantaneous frequency can be solved by HHT [8,9]. For BIMF, it is a kind of multi-component, it needs to be transformed by Hilbert transform to get the amplitude and phase of the image. For the \( i \)th BIMF component, it will be represented as a complex value simple-component:

\[
Z_i(t) = D_i(t) + j \cdot H(D_i(t)) = a_i(t)e^{\theta_i(t)}
\]

where \( r = [m, n]^T \), \( D_i(t) \) is the \( i \)th BIMF, \( H(D_i(t)) \) is the 2D Hilbert transformation, \( a_i(t) \) is the amplitude modulation function of BIMF, \( \theta_i(t) \) is the phase modulation function of BIMF.

Local instantaneous frequency can be computed using phase modulation function. Because phase modulation function is 2D, so instantaneous frequency is directional, local horizontal instantaneous frequency and local vertical instantaneous frequency can be achieved taking the derivative of horizontal and vertical instantaneous frequency:

\[
f_m = \frac{\partial}{\partial m} \theta_i(t), \quad f_n = \frac{\partial}{\partial n} \theta_i(t)
\]

The instantaneous frequency of BIMF component makes use of the solved local horizontal instantaneous frequency and local vertical instantaneous frequency. The root-mean-square of local horizontal instantaneous frequency and local vertical instantaneous frequency of BIMF are selected as the instantaneous frequency features. It is available to show local point information; its definition is shown as follows:

\[
E(m, n) = \sqrt{\left( \frac{\partial}{\partial m} \theta_i(t) \right)^2 + \left( \frac{\partial}{\partial n} \theta_i(t) \right)^2}
\]

2.3. Key issues of BEMD

2.3.1. Plane interpolation method

In BEMD, discrete points are processed by interpolation to get fitting surface. Its main methods include triangulation combined linear interpolation and radial basis function interpolation. In 2D space, triangulation interpolation is that the interpolation region is segmented into small triangle regions, interpolation surface is constructed in small triangles, and small triangles are spliced to get a big interpolation surface. The extrema in the image are regarded as discrete points to rebuild surfaces in radial basis function interpolation.

Its general solution is:

\[
s(t) = p(t) + \sum_{i=1}^{N} \lambda_i\phi(||t - t_i||)
\]

where \( p(t) \) is the first order polynomial, by solving first \( N + 3 \) order linear system of equations, combination coefficient \( \lambda_i \) and monomial coefficient \( c_i \) of radial basis function can be achieved. The entire interpolation surface is achieved substituting all points coordinate values. Triangulation interpolation is fast, but has large errors in the low-frequency image. It is fit for decomposing high-frequency parts in high-frequency image. Radial basis function interpolation is fit for low-frequency image with less extrema.

In plane interpolation, the extrema are processed by Delaunay triangulation. Cubic interpolation is introduced in the divided triangles. The advantages of the method based on triangulation and cubic interpolation are as follows: firstly, extrema (the maximum or the minimum) used for interpolation are not must square mesh and the extrema in an image are normally discrete, irregular; On the other hand, the interpolation plane from the method is not smooth, in fact, it is 2D plane interpolation.

The extrema symmetric extension is proposed in this paper to prevent end effect of BEMD. Edge of the image is regarded as symmetry axis, and extrema around edges are expended. Extension is to make the decomposed data completely and the errors around four edges are reduced to propagate inwardly.

2.3.2. The stop condition of screening process of BEMD

The number of zero crossing points in BIMF is not easy to statistics, so the constraint condition of BIMF can be regarded as the stop
condition of screening process of BEMD. Cauchy-type convergence conditions and energy difference trace can also be used as the stop condition. In this paper, Cauchy-type convergence conditions are selected, and SD is 0.3.

The stop condition of screening process is: SD is used for representing the standard deviation. For 2D BEMD, SD is shown as the following formula (6). If SD is less than the threshold, the screening process stops.

\[
SD = \sum_{x} \sum_{y} \frac{(h_{k-1}(x,y) - h_k(x,y))^2}{h_{k-1}^2(x,y)}
\]

where \( x, y \) are the width and height of the image. Standard deviation is based on the convergence of BEMD. In screening process, \( h_k(x,y) \) is more and more close to IMF components steadily. So, the numerator in formula (6) is more and more close to zero, it means that SD is close to zero finally.

2.4. BIMF component classifier

Fig. 1 is an example of BEMD, Fig. 1(a) is decomposed into 9 layers, Fig. 1(b–j) are BIMF components from the first layer to the 9th layer and Fig. 1(k) is the residue component. BEMD has the following advantages:

(1) The decomposed images achieved by BEMD are from fine to coarse and undistorted, its results are ideal and it is good for texture extraction.

(2) The image is divided into small parts and large coefficient matrix is changed into small matrix during every screening process. It can save memory space of matrix efficiently.

(3) The computing speed is improved by the way of dividing image into small parts.

For BIMF components are extracted layer-by-layer, it is local frequency is from high to low values. Local frequency of BIMF components includes some strong contrast physical information, such as highlight edges of source images, line and zone boundary, etc. In this paper, image features are extracted from 2D BIMF components based on dual-channel PCNN. The features are used for fusing image and improving fusion results.

Each BIMF component contains different frequency coefficients, the lower the order of the BIMF, the more high-frequency coefficients contains. Coefficients magnitude of different BIMF components varies greatly. So BIMF's energy can be adopted as a feature to classify the components. Parseval’s theorem is used to obtain the energy of the original image (\( E_1 \)) and the energy of each IMF component (\( E_i \)); \( R_i \) can be selected as the classification criteria.

\[
R_i = \frac{E_i}{E_1}
\]

(8)

\[
E_i = \sum_{j=0}^{s-1} I_j^2
\]

where \( I_i \) is the amplitude of the amplitude spectrum, \( S \) is the number of coefficients which the component contains, \( i \) is the layers number of BIMF components.

The number of image decomposition layers decides the amount of images information of the BIMD and residue components contain. Fig. 1(a) is decomposed into 1–4 layers respectively, Fig. 2(a–h) are the BIMF and residue components. Fig. 2(e–h) shows that the more layers, the less information the residue component contains. For further analysis, Fig. 1(a) is decomposed into 9 layers in this paper; Fig. 3 shows the energy distribution corresponding to the respective layers component. The energy contains in the components of the different layers are different, the former three and the residue component contain larger energy than others.

The relationship between the energy and the image information can be shown in Fig. 4(a–f), are the different layers of BIMF components superimposed the residue component. Fig. 4(c–e) is almost no difference which proves that less energy the component has less information the component contains.

In this paper BIMF components are divided into two categories: high-frequency and low-frequency components accordance with their energies, if the formula (9) is satisfied, the components will be selected as the high-frequency components, the remaining BIMF components are selected as the low-frequency components.

\[
\begin{align*}
T_j &= \frac{\sum_{i=1}^{j} E_i}{E} > 90\% \\
E_i \frac{E}{E_{i+1}} &< 5, \quad i = 1, 2, \ldots n - 1
\end{align*}
\]

where \( T_j \) represents the proportion of the first \( j \) layers BIMF components and the total energy, \( j \) represents the layer number of satisfy the conditions of the high-frequency components, \( n \) represents BIMF layer number component.
3. Dual-channel PCNN

PCNN has complex structure and needs to set many parameters [10], even the improved simplified model has shortcomings of uneven brightness zone resolution, and it’s not conducive to dim image information extracting [11,12]. In contrast, dual-channel PCNN has an advantage in this regard [13]. The low-frequency components are significantly dim compare with other components.

The dual-channel PCNN is different from PCNN in composition of neurons, as shown in Fig. 5:

The dual-channel PCNN neurons include: the receptive field, modulation domain and pulse generating domain. The dual-channel PCNN can be expressed as follows:

The receptive field:

\[ F_y[n] = S_y[n] \]  
(10)

\[ F_x[n] = S_x[n] \]  
(11)

\[ L_y[n] = e^{-\alpha_L} L_y[n-1] + V_l \sum_{kl} w_{ylk} Y_{kl}[n-1] \]  
(12)

modulation domain:

\[ U_y[n] = \max \{ F_y[n](1 + \beta_y U_y[n]), F_y[n][1 + \beta_y U_y[n]] \} \]  
(13)

pulse generating domain:

\[ Y_y[n] = \begin{cases} 1, & U_y[n] > T_y[n] \\ 0, & \text{otherwise} \end{cases} \]  
(14)

\[ T_y[n] = e^{-\alpha_T} T_y[n-1] + V_T Y_y[n] \]  
(15)

where \( F_y \) and \( F_x \) are external outputs, \( S_y[n], S_x[n] \) represent the input stimulus, \( n \) represents the number of iterations, \( L_y \) is the linking input, \( \beta \) is the linking weight, \( w_{ylk} \) is the synaptic connections, \( V_l, V_T \) are normalization constants, \( Y_y \) is the pulse output of the neuron, its value is 0 or 1, \( T_y \) is the dynamic threshold, \( \alpha_L, \alpha_T \) is the constant, \( U_y \) is the firing mapping image, and it is the internal activity of neuron. The final image can be achieved using \( U_y \). If \( U_y[n] > T_y[n] \), the neuron generates a pulse, called a firing. In fact,
after n iterations, the number of firings of the neuron is used to represent the information of the image at the corresponding point. Firing map is constructed by the number of firings and is regarded as output of dual-channel PCNN.

Aim to shortcomings of PCNN model in image fusion domain, combines with the characteristics of multi-focus image, this paper proposes the dual-channel PCNN which are motivated by low-frequency components of BIMF. The low-frequency components reflect the image details; details of the original images can be better reflected in the fused image.

4. Medical image fusion based on BEMD and dual-channel PCNN

Medical image is severely affected by the noise, the contrast of the image is low and it is difficult to distinguish the details by the human eye. So the fusion method needs to consider the particularities of the medical image. In BEMD, medical image is decomposed into BIMF components and a residue component. They represent different physical meanings: the residue component is the approximate representation of the medical image gray value and it contains the texture information, BIMF components represent the edge and structural information of the medical image, there are significant differences among BIMF components. To compare the medical image with the other images, CT and MR images are decomposed into 9 layers in this paper, Fig. 6 shows the energy distribution of each layer, and it is significantly different to Fig. 4, the residue component contains less image information and there are significant differences among BIMF components, Fig. 7 shows the superimposing results of different decomposed layers of Fig. 6(b), Fig. 7(a–c) have significant discrepancies in their respective energies, the differences of the image are obvious. Fig. 7(c–e) have approximately equivalent energies, they are difficult to distinguish, BIMF components can be classified as high frequency and low frequency components, the high frequency components contain more textures, which have larger energy and have been affected by noise seriously, low frequency components have less energy but contain the edge information. BIMF components can be divided into the low frequency and high frequency components based on energy of the components, and then fusion rules are built respectively, in this way the contrast of the image will be enhanced and the edge and structure information of the medical image will be protected, the fused image will contain rich image textures and details.

The fusion rules are built to fuse the BIMF components and the residue component respectively, suppose N is the times of iteration of dual-channel PCNN and detailed fusion steps are as follows:

1. Registration medical image A and B are decomposed by BEMD and getting a series of BIMF components and a residue component;
2. BIMF components are divided into two categories according to formula (9): low frequency and high frequency components;
3. High frequency components and the residue component are superimposed;
4. Low frequency components are input into dual-channel PCNN to select the low frequency fusion coefficients;
5. Initialization: \( L_d^{ij}[0] = 0, \ U_d^{ij}[0] = 0, \ \theta_d^{ij}[0] = 0, \ \gamma_d^{ij}[0] = 0, \ \eta = 0.4, d \) is the dth layer.
6. According to formulas (10–15), \( L_d^{ij}[n], U_d^{ij}[n], \ \theta_d^{ij}[n], \ \gamma_d^{ij}[n] \) are calculated.
7. If \( n = N \) is satisfied, the iteration finishes. The selection rule of fusion coefficients is as follows:

\[
\text{Coeff}^d = \begin{cases} 
\text{Coeff}^A, & \text{if} U_d^{ij}[n] = F_{A,d}^{ij}[n] \left[ 1 + \beta_{A,d}^{ij}L_d^{ij}[n]\right] \\
\text{Coeff}^B, & \text{if} U_d^{ij}[n] = F_{B,d}^{ij}[n] \left[ 1 + \beta_{B,d}^{ij}L_d^{ij}[n]\right]
\end{cases}
\]

Fig. 6. Energy distribution and energy ratio of different components.

Fig. 7. Components selectively superposition (a) the first layer, (b) the first two layers, (c) the first 3 layers, (d) the first 9 layers, (e) the source image.
5. Experimental results and analysis

Three groups’ experiments are done to verify the proposed algorithm in the paper. Every group’s experimental images are registrated [14]. Fig. 6(a and b) is the source image in the first group experiment. Fig. 6(a) is CT image, Fig. 6(b) is MR image; Fig. 9(a–d) is the source images of the second and the third group experiments. Fig. 9(a and c) is CT images; Fig. 9(b and d) is MR images. All these images are considered as referenced images to compare with fusion images attained from the proposed algorithm in the paper and other algorithms.

5.1. Objectivity evaluation index

5.1.1. Mutual information

Mutual information expresses how much information of source image is fused into the result image [15]. The larger the mutual information is, the better the fusion effect. Supposed that A and B are source images and F is the fused image, then the calculation of mutual information between A and F, B and F are respectively shown as formulas (17) and (18):

\[ I_{AF} = \sum_{a, f} p_{AF}(a, f) \log \frac{p_{AF}(a, f)}{p_{A}(a)p_{F}(f)} \]

\[ I_{BF} = \sum_{b, f} p_{BF}(b, f) \log \frac{p_{BF}(b, f)}{p_{B}(b)p_{F}(f)} \]

where \( p_{AF} \) and \( p_{BF} \) are joint histogram of the source images and F, \( p_{A} \), \( p_{B} \), and \( p_{F} \) are respectively the histogram of A, B, and F respectively at the pixel values of respective image. The calculation of mutual information is shown as formula (19):

\[ MI = I_{AF} + I_{BF} \]

5.1.2. \( Q^{AB/F} \)

\( Q^{AB/F} \) expresses how much edge information is fused from the source image into the fusion image [16]. The larger the value of \( Q^{AB/F} \) is, the more edge information will be fused into the fusion image. The better fusion result is achieved. \( Q^{AB/F} \) is shown as formula (20):

\[ Q^{AB/F} = \frac{\sum_{n=1}^{N} \sum_{m=1}^{M} (Q^A(n, m)w^A(n, m) + Q^B(n, m)w^B(n, m))}{\sum_{i=1}^{N} \sum_{j=1}^{M} (w^A(i, j) + w^B(i, j))} \]

\( Q^A(n, m) = Q^A_g(n, m)Q^A_d(n, m) \) with \( 0 \leq Q^B(n, m) \leq 1 \), \( Q^A_g(n, m) \) and \( Q^A_d(n, m) \) model perceptual loss of information in F, in terms of how well the strength and directional values of a pixel \((n, m)\) in A or B are represented in the fusion image. If \( A = 0 \), it corresponds to the complete loss of edge information at location \((n, m)\) as transferred from A or B into F. If \( A = 1 \), it indicates “fusion” from A to F with no loss of information. \( w^A(n, m) \) and \( w^B(n, m) \) reflect the importance of \( Q^A(n, m) \) and \( Q^B(n, m) \).

5.2. Analysis of fusion results

The fusion results of the first group experiment are shown in Fig. 10. Fig. 10(a) is the fusion result using the proposed method. Fig. 10(b–f) are the fusion images based on the Laplacian (Lap) method, discrete wavelet transform (DWT) method, shift invariant DWT (SIDWT) method, gradient pyramid and ratio pyramid method, respectively. In Fig. 10(a–f), it is evidently to find that the fusion image of the proposed method is clearer than other methods. Moreover, the fusion result of DWT-based method, as shown in Fig. 10(c), introduces many ‘artifacts’ around edges because DWT lacks shift-invariance. It is proven that the proposed method can decrease the pseudo-Gibbs phenomena successfully and improve the quality of the fusion image. Fig. 10(b) indicates that the Laplacian-based method provides better performance in fusion medical images compares with DWT-based. However, from Fig. 10(b) is not extracted all useful information of the source.
images perfectly. Above all, Fig. 10(a) has the best visual quality and contains most of the useful information of the source images, and meantime, fewer artifacts are introduced during the fusion process.

The fusion results of the second and the third group experiments are shown as Figs. 11 and 12. Fig. 11(a–f) and Fig. 12(a–f) are the fusion images based on the above methods, respectively. Fig. 11(a) and Fig. 12(a) show the proposed method conveys more useful information from the source images to the fusion image when compares with the other methods.

For further comparison, besides visual observation, two objective evaluation indexes are used to compare the fusion results. The first evaluation index is the mutual information (MI). It is a metric defined as the sum of mutual information between each input image and the fused image. The second evaluation index is QAB metric, which considers the amount of edge information transferred from the input images to the fused image. This method uses a Sobel edge detector to calculate strength and orientation information at each pixel in both source and the fusion images. In comparison, Tables 1–3 show the objective criteria on mutual information (MI) and QAB of Figs. 10–12. The indexes show that the proposed method has the best fusion results.

6. Conclusion

BEMD is a data-driven function, medical image features can be extracted from decomposed components, and it is fit to process two-dimensional non-linear and non-steady-state data. In this paper, medical images are decomposed by BEMD, image feature extraction is based on BIMF and the residue components, low-frequency fusion coefficients are selected based on the dual-channel PCNN. All of the comparisons indicate the proposed method contain more image features; more details are preserved in the fusion process. From analysis above, the conclusion is that the proposed algorithm also shows significant improvement over the traditional fusion methods, whether in subjective evaluation or objective evaluation criterion.

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