

MRI Image Fusion Method based on Classification of BEMD Components

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Abstract

In this paper, MRI image fusion based on bi-dimensional Empirical Mode Decomposition and dual channel Pulse Coupled Neural Networks (PCNN) is performed. Intrinsic Mode Function (IMF) components are decomposed into high frequency and low frequency components based on energy levels. The resultant fusion coefficients are attained using fusion rule. High frequency and residue components are superimposed to acquire more textures. Low frequency components contain more particulars of source image and are given as input to dual channel PCNN. The resultant fused image can be achieved by inverse transformation of Bi-dimensional Empirical Mode Decomposition (BEMD). It is a self-adaptive tool used for analysing nonlinear data.

Keywords— BEMD, Empirical Mode Decomposition, Intrinsic Mode Function, PCNN

I. INTRODUCTION

MRI image fusion is an emerging topic in medical image processing domain. All medical image information is pooled to process the fusion of multimodality image that supports to find more valuable information. Medical image fusion aims at fusion of images like CT and MRI, SPECT and MRI, SPECT and CT form of multimode medical images. Wavelet transform is generally used at medical image fusion. Wavelet transform has only medium spatial and frequency characteristics. Hence empirical mode decomposition is the preferred choice. This decomposition process has better spatial and frequency characteristics. But in EMD, screening edges will have large errors and data series are contaminated. So in order to get data without errors, Bi-dimensional Empirical Mode Decomposition is used to get better performance. BEMD is used with dual channel pulse coupled neural network to obtain further computational performance. PCNN will help in selecting only the low frequency components. BEMD will decompose the input image into BIMF components of various levels. MRI has a wide range of applications in medical diagnosis and there are assessed to be over 25000 scanners in use worldwide. MRI has impact on diagnosis and treatment in many specialities even though effect on improved health outcomes is indeterminate. Since MRI does not use any ionizing radiation, its use is recommended in preference to CT when either modality could yield equivalent information. MRI is a safe technique but number of incidents causing patient harm has increased. The safety of MRI during first trimester of pregnancy is ambiguous but it may be preferable to alternative options. It is also used to understand how different parts of brain respond to stimuli. Blood

oxygenated level dependent of MRI measures hemodynamic response to transient neural activity, which results from change in ratio of oxyhaemoglobin and Deoxyhaemoglobin. It is used to construct 3D parametric map of brain signifying those regions of cortex which demonstrate a significant change in activity in response to task.

II. LITERATURE SURVEY

Huang proposed the Empirical Mode Decomposition (EMD) in the year 1998 for the multi-scale analysis of signals. It is an iterative method that decomposes the input signal into different intrinsic mode function (IMF) [1]. EMD is an adaptive method which can be applied to analyze non-linearity and non-stationary signals [2]. One dimensional EMD with superior physical features can be expanded to analyse two dimensional signals [3]. This decomposition is the estimation of upper and lower envelopes as interpolated curves between extrema. Cubic splines are preferred for doing the interpolation. It also operates for discrete time signals. EMD will satisfy two requirements. The number of IMF's extrema and number of zero crossings must either be equal to or at differ at most by one. This iteration is continued until the mean value of envelope defined by local maxima and envelope defined by local minima shall be zero [4].

EMD is applied to the signal and decomposed into various IMFs. For uniforming the amplitude and in over decomposing it is by spreading out its components over adjacent modes. More over hierarchical and nonlinear nature conveys that there is no means guarantee that EMD signals would be concatenation of individual EMD [5]. This variation is also referred as Local EMD. Its drawback is medium spatial and frequency characteristics. Texture and edge characters do not appear in EMD.

III. PROPOSED METHODOLOGY

BIMF components can be categorized as high frequency and low frequency components depending on the energy level. The high frequency components contain more textures, which have larger energy but it is largely affected by noise [6]. Low frequency components have less energy but contain the edge information.

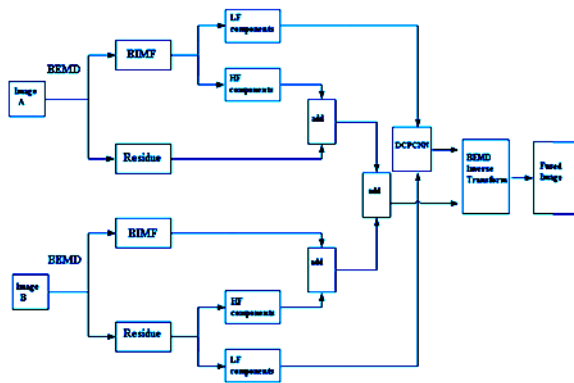


Fig. 1 A MRI image fusion method using BEMD and DCPNN

The divided BIMF components of low frequency and high frequency components are then fused using fusion rules. Thus the contrast of the image will be enhanced and the edge and structure information of the medical image will be protected. The resultant fused image will contain rich image textures and details. Fig. 1 shows the MRI fusion method using BEMD and DCPNN.

BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION (BEMD)

BEMD is a kind of completely self-adaptive tool. BEMD encounters two requirements: Number of maximum and minimum points is equal to zero crossing points. Mean of envelope constituted by minimum and maximum is close to zero. Steps for BEMD algorithm are as follows

- A. Initialise the residue components $R=I$, I is the source image
- B. If the residue R is monotone or it reaches decomposition number of an image the algorithm stops
- C. The extrema in image P are achieved maximum points set and minimum point set in the region are searched
- D. The maximum and minimum point set are plane interpolated and upper and lower enveloping surfaces of image are achieved
- E. $M(m, n) = (U(m, n) + L(m, n)) / 2$
- F. $H_k(m, n) = H_{k-1}(m, n) - M(m, n)$ this condition is used for stopping the process. If this condition is not satisfied go to step 3.

III. Plane interpolation method

There are many interpolation methods available for the joining of decomposed extrema levels. Out of this, triangulation interpolation method is faster but has large errors in low frequency components of the image. Cubic interpolation is introduced in divided triangles. This method has the advantages as extrema used for interpolation are not must square mesh and extrema are normally discrete [7].

BIMF COMPONENT CLASSIFIER

Advantages of BIMF component classifier are:

The decomposed images achieved by BEMD are from fine to coarse and undistorted. Its results are ideal and it is good for extraction. The image is divided into small parts and large coefficients matrix is changed into small matrix during every screening process. It can save memory space of matrix efficiently. The computing speed is improved by the way of dividing image into smaller parts. A BIMF component contains two different coefficients. They are lower and higher frequency components.

DUAL CHANNEL PCNN

PCNN neurons include three domains like receptive field, modulation domain and pulse generating domain

Receptive field:

$$F_{ij}^A[n] = S_{ij}^A[n] \quad (1)$$

$$F_{ij}^B[n] = S_{ij}^B[n] \quad (2)$$

$$L_{ij}[n] = e^{-\alpha L} L_{ij}[n-1] + V_L \sum W_{ijkl} Y_{kl}[n-1] \quad (3)$$

Modulation domain:

$$U_{ij}[n] = \max(F_{ij}[n](1 + \beta_{ij}[n]L_{ij}[n]), F_{ij}[n](1 + \beta_{ij}[n]L_{ij}[n]))$$

Where F_{ij} is external outputs, S_{ij} represent the input stimulus, n is the number of iterations, L_{ij} is the linking input. β is the linking weight, W_{ijkl} is the synaptic connections.

Pulse generating domain:

$$Y_{ij}[n] = \begin{cases} 1, & U_{ij}[n] > T_{ij}[n] \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

MEDICAL IMAGE FUSION BASED ON BEMD AND DUAL CHANNEL PCNN

Image A and image B are decomposed by BEMD. After decomposition, series of BIMF components and residue components are obtained from both the images. In image A BIMF component are divided into two categories low and high frequency components. High and residue components are superimposed. In Image B residue is divided into high and low frequency components. BIMF and high frequency components are superimposed. Low frequency components from both images are input to Dual Channel PCNN. Both superimposed components are once again superimposed. To select low frequency coefficients, superimposed and DCPNN coefficients are transformed into fused image based on BEMD inverse transform.

V. RESULTS AND DISCUSSION

To the input image BEMD is applied. Its spectrum is obtained in fig 2. BIMF components divide the input into different modes and reconstructed composite. To reconstruct the image composite DCPNN is applied. Fig. 3 to 8 shows the decomposed images obtained using BEMD.

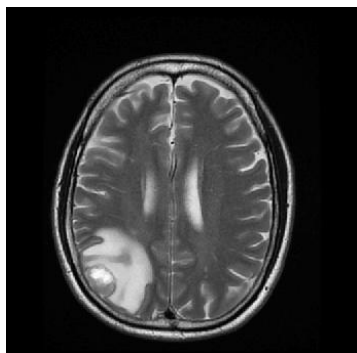


Fig1 Input Image

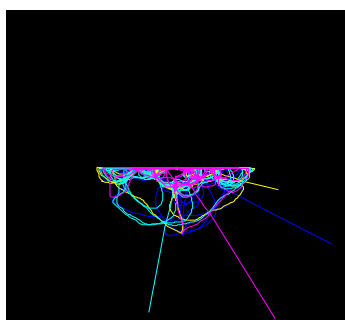


Fig 2 Input spectrum

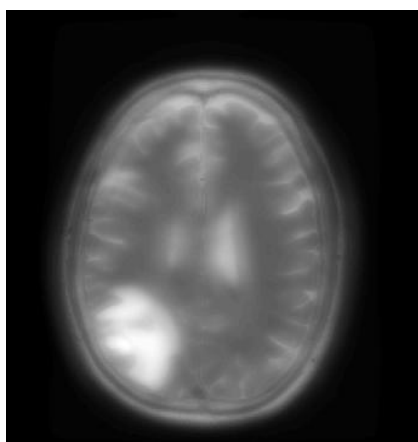


Fig 3 Mode1

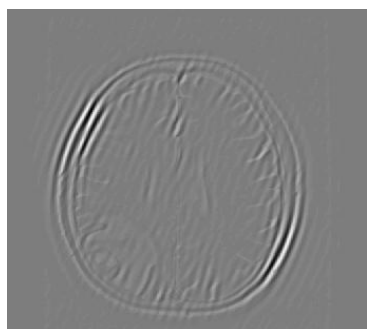


Fig 4 Mode 2

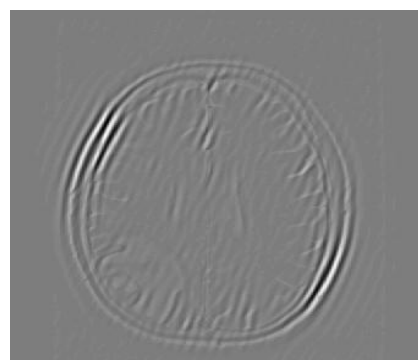


Fig 5 Mode 3

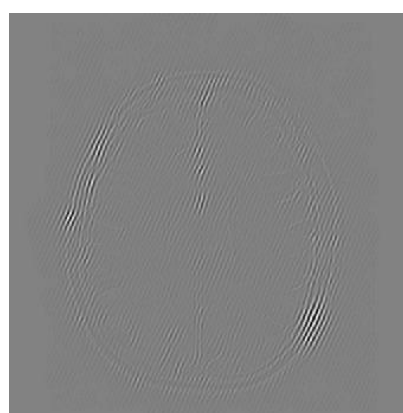


Fig 6 Mode 4

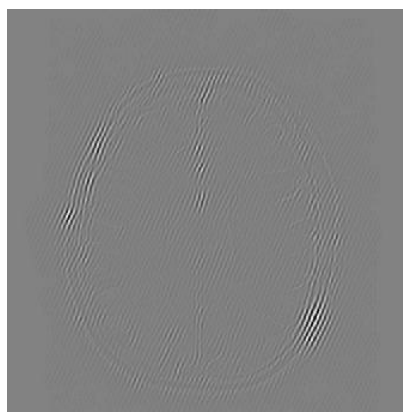


Fig7 Mode 5

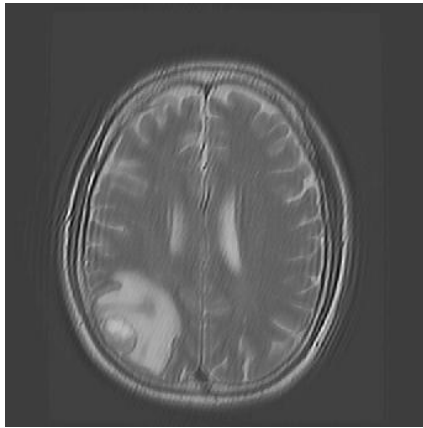


Fig8Recostruced Composite image

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Conclusion

BEMD is a data based adaptive function that is applicable to both signal and images. 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, MRI images are decomposed by BEMD, image feature extraction is performed based on BIMF and the residue components, low-frequency fusion coefficients are selected based on the Dual Channel PCNN. More details are preserved in the fusion process. It is shown 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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