EMD Based Multi-scale Model for High Resolution Image Fusion

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Abstract  High resolution image fusion is a significant focus in the field of image processing. A new image fusion model is presented based on the characteristic level of empirical mode decomposition (EMD). The intensity hue saturation (IHS) transform of the multi-spectral image first gives the intensity image. Thereafter, the 2D EMD in terms of row-column extension of the 1D EMD model is used to decompose the detailed scale image and coarse scale image from the high-resolution band image and the intensity image. Finally, a fused intensity image is obtained by reconstruction with high frequency of the high-resolution image and low frequency of the intensity image and IHS inverse transform result in the fused image. After presenting the EMD principle, a multi-scale decomposition and reconstruction algorithm of 2D EMD is defined and a fusion technique scheme is advanced based on EMD. Panchromatic band and multi-spectral band 3,2,1 of Quickbird are used to assess the quality of the fusion algorithm. After selecting the appropriate intrinsic mode function (IMF) for the merger on the basis of EMD analysis on specific row (column) pixel gray value series, the fusion scheme gives a fused image, which is compared with generally used fusion algorithms (wavelet, IHS, Brovey). The objectives of image fusion include enhancing the visibility of the image and improving the spatial resolution and the spectral information of the original images. To assess quality of an image after fusion, information entropy and standard deviation are applied to assess spatial details of the fused images and correlation coefficient, bias index and warping degree for measuring distortion between the original image and fused image in terms of spectral information. For the proposed fusion algorithm, better results are obtained when EMD algorithm is used to perform the fusion experience.

Keywords  image fusion; experimental model decomposition; quantitatively evaluation

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Introduction

With the development of remote sensing, spatial and spectral resolution and temporal resolution of images have become greatly improved[1]. The remote sensing image is available from different remote sensors and how to make the best of the information from these multi-source and multi-resolution images is one of the significant issues in the application of remote sensing[2]. Image fusion effectively enhances the available information with these data, and supplies a basis for target recognition and information extraction. So far, lots of image fusion schemes between high-resolution panchromatic image and low-resolution multi-spectral image have been proposed by academicians. Traditional fusion schemes include IHS[3,4], PCA[5], and so on. In recent years, multi-scale fusion models combined with pyramid or wavelet fusion framework have become widely used.
and have strong advantages\cite{6-8} because the characteristics of the different scales are merged by multi-scale fusion models to improve the fusion effects.

The EMD presented by Huang et al. in 1998 is a new time-frequency analysis tool that can be considered as a local time-frequency analysis method. Signals in the EMD can be broken up into limited empirical mode function according to its characteristic, which is especially suitable for non-stationary signal analysis\cite{9,10}. However, the research and application of two-dimensional EMD decomposition is not yet mature\cite{11}. A remote sensing image can be considered as a two-dimensional non-stationary signal and can be decomposed into different frequency signals based on EMD method as has been used to de-noise images with the row-column decomposition scheme\cite{12}. A new image fusion model is proposed by integrating the multi-scale fusion concept and EMD theory. Then, the experimental verification of the model using a high-resolution image is given.

1 Theoretical principle

1.1 Empirical mode decomposition

The IMF decomposed by EMD of a given signal\cite{9,13} satisfies these two conditions: ① having the number of extrema and the number of zero-crossings equal (or differing at most by one); ② having symmetric envelopes defined by the local minima and maxima. The signal can be expressed as the sum of IMF and the residual. The decomposition of a signal \(x(t)\) can be written as:

\[
x(t) = \sum_{i=1}^{n} f_i(t) + r_i(t)
\]

where \(f_i(t)\) denotes the \(i\)th IMF components constrained to be zero-mean and \(r_i(t)\) stands for a residual “trend”. The intrinsic mode decision is based on automatic and adaptive (signal-dependent) time-variant filtering and their high versus low frequency discrimination applies only locally and corresponds in no way to a pre-determined sub-band filtering (e.g., in a wavelet transform). The effective algorithm of EMD can be summarized as follows: ① identify all extrema of \(x(t)\); ② generate envelope \(e_{max}(t)\) by interpolating between minima; ③ calculate mean value with \(m(t) = (e_{max}(t) + e_{min}(t))/2\); ④ extract detail \(d(t) = x(t) - m(t)\); ⑤ iterate steps ① to ④ on \(d(t)\) until it is zero-mean according to some stopping criterion, then the obtained \(d(t)\) is referred to as an IMF; ⑥ calculate \(m(t) = x(t) - f_i(t)\); ⑦ iterate steps ① to ⑥ until IMF is not available.

1.2 Framework of multi-decomposition and reconstruction of EMD

Further investigation of the algorithm is demonstrated in the study in view of the multi-resolution analysis ability of EMD. The IMF calculation operator and residual calculation operator are defined as \(F_{\text{imf}}()\) and \(F_{\text{residual}}()\) with EMD algorithm, where the two operators are similar to high-frequency filter and low-frequency filter. Operator \(F_{\text{imf}}()\) includes EMD decomposition steps from ① to ⑤ with the view of obtaining a high frequency of the specific scale, \(F_{\text{residual}}()\) stands for step ⑥, that is, by calculating the residual, a low frequency of the corresponding scale is obtained. Then, a multi-resolution structure is realized by decomposing the low frequency step by step. The decomposition formula from \(i\)th to \((i+1)\)th is given as:

\[
f_{i+1}(t) = F_{\text{imf}}(m_i(t))
\]

\[
m_{i+1}(t) = F_{\text{residual}}(m_i(t))
\]

and the reconstruction is expressed as:

\[
m_i(t) = F_{\text{imf}}^{-1}(f_{i+1}(t)) + F_{\text{residual}}^{-1}(m_{i+1}(t))
\]

where \(F_{\text{imf}}^{-1}()\) and \(F_{\text{residual}}^{-1}()\) denote the inverse operator of \(F_{\text{imf}}()\) and \(F_{\text{residual}}()\), respectively. The multi-scale analysis structure given by EMD theory can be denoted with Fig.1.

Fig.1 EMD based multi-scale decomposition structure

The advantages of EMD are the characteristic of data driving decomposition which is different from traditional filters. The results of EMD have been proved to be suitable for finding physical meaning of the real process. The periodical information and the in-
stantaneous frequency characteristic analysis of the signal can be demonstrated with the multi-scale EMD structure. The EMD model has found its way in various applications with great success, especially in signal prediction, break detection and signal decomposition.

2  Image fusion scheme based on EMD

The EMD multi-scale decomposition of an image is first processed by EMD decomposition line by line, reconstructing a high frequency characteristic image $High_{row}$ by selecting the appropriate high frequency mode part. The first decomposition scale image can be given and the remaining section is treated as the low frequency characteristic image $Low_{row}$. The high-frequency characteristic image $High_{column}$ and low-frequency characteristic image $Low_{column}$ of the second decomposition scale is obtained by the column EMD decomposition of $Low_{row}$. The third scale is obtained by the column EMD decomposition to $Low_{column}$. The process is iterated to realize the sequential multi-scale decomposition of the image.

Based on 2D EMD realized by row-column decomposition, the improved IHS image fusion scheme is described as Fig.2. First, PAN image is selected as the base image for geometric registration of the multi-spectral bands, resampling into PAN band resolution, then intensity, hue, and saturation image can be obtained by IHS transform to the multi-spectral RGB image. The steps of the image fusion is as follows.

1) $I$ is considered as the base image for adjusting the histogram of PAN to obtain the PAN$^{IMP}$ with the same equal and variance of $I$. IMP is short for improved panchromatic image.

2) The traditional row column of the $I$ and PAN$^{IMP}$ are selected to process EMD decomposition and define the retained high frequency mode layers by unified selection criterion or different selection criterion according to the actual complexity of the row and column.

3) To obtain the $High_{row}$($High_{column}$) with the row-wise (column-wise) and $Low_{row}$($Low_{column}$) with the row-wise (column-wise), the image is decomposed with row EMD or column EMD, extracting the multi-scale high and low frequency characteristic image information.

4) Obtaining the enhanced fused intensity image (FI) for getting the RGB multi-spectral image by IHS inverse transform, the $High_{row}$($High_{column}$) of the high resolution image and the $Low_{row}$($Low_{column}$) of the $I$ band image is selected for reconstruction.

3  Quantity evaluation of the fused image

The purpose of the imagery fusion is to improve the spatial resolution as high as possible and simultaneously maintain the multi-spectral characteristic for...
culture recognition and classification. The evaluation method is both the visual evaluation which is the method of the qualitative evaluation by visualization comparison and quantity evaluation. The spatial resolution is all enhanced with different fusion schemes in Fig.3. At the same time, there is no obvious spectral difference except the Brovey algorithm. Researchers have proposed some qualitative evaluation methods owing to its drawback of subjective evaluation. The standard of qualitative evaluation is used for measurement to maintain the multi-spectral characteristic information and high resolution spatial information. The qualitative evaluation index in the study is as follows.

3.1 Shannon entropy

Entropy is a synthetic index for imagery information contents. For the 8-bits image, Shannon entropy is defined as:

\[ H(x) = - \sum_{i=0}^{255} p_i \log_2 p_i \]  

where \( p_i \) is the probability of gray level \( i \) in the evaluated region approximately given by:

\[ p_i = \frac{f_i}{N} \]  

where \( f_i \) is the frequency of gray level \( i \); \( N \) denotes the total pixels of the image. The higher value of Shannon entropy, the more textural information of the fused images, which indicates a better merger.

3.2 Standard deviation

A performance measure \( \sigma \) is defined as the standard deviation of the difference image between the fused image and the low spatial resolution MS bands:

\[ \sigma = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} [F(i,j) - L(i,j)]^2}{MN}} \]  

where \( M, N \) is the dimensions of the imagery; \( F(i,j) \) and \( L(i,j) \) denote the gray value of the fused and the low spatial resolution image respectively. The lower the value of the parameter, the better spectral quality of the merged image. They should be as close to 0 as possible.

3.3 Correlation coefficient

Correlation coefficient is used to evaluate the correlation between the fused image and the original image. Their correlation is strong if the correlation coefficient of the imageries and correlation coefficient is defined as:

\[ c(A, B) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - \mu(A))(x'_{ij} - \mu(B))}{\sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - \mu(A))^2 \sum_{i=1}^{n} \sum_{j=1}^{m} (x'_{ij} - \mu(B))^2}} \]  

where \( A \) and \( B \) are two images; \( x_{ij} \) and \( x'_{ij} \) are the pixel values of two images; \( \mu(A) \) and \( \mu(B) \) are the average pixels.

3.4 Deviation index

Deviation index is defined as the mean absolute value of the ratio between the difference of the fused band and multi-spectral bands to multi-spectral band.

\[ B_{\text{bias}} = \frac{1}{m \times n} \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{|x_{ij} - x'_{ij}|}{x_{ij}} \]  

where \( x_{ij} \) and \( x'_{ij} \) are the pixel values of the original multi-spectral image and fusion image. The index measures the deviation between the multi-spectral image and fusion image. The bigger deviation index suggests the worse fusion quality.

3.5 Distorting index

Distorting index, which expresses the distortion of fusion image compared to multi-spectral image, is defined as:

\[ W = \frac{1}{m \times n} \sum_{i=1}^{n} \sum_{j=1}^{m} |x_{ij} - x'_{ij}| \]  

where \( x_{ij} \) and \( x'_{ij} \) are the pixel values of the original multi-spectral image and fusion image. The distortion becomes more serious with the increase of \( W \) value.

4 Experimental results

The Quickbird image of the local region in Shanghai is selected for the fusion experiment (Fig.4). First, the PAN band image and intensity band image obtained with IHS transform from multi-spectral band 3,2,1 are analyzed. Six empirical modes (Fig.3) can
be calculated with EMD to the selected representative two lines of pixel gray value time series. The figure shows that the PAN image has more details than the intensity band in the first two modes. However, in the third to the sixth mode, it is mainly expressed as trend information. Then, decomposition modes of the PAN are as much as the intensity bands in the last three modes. Therefore, the first empirical mode of the row-column decomposition in PAN is selected as high frequency information which holds the first and second mode information of the PAN after one multi-scale EMD decomposition in row and column.

That is to say, the High$^\text{low}$ and Low$^\text{low}$ are obtained from the first mode of I band image after one row-wise decomposition. The column-wise decomposition of the Low$^\text{row}$ obtains the High$^\text{column}$ and Low$^\text{column}$ of the high frequency image by keeping the first mode information. The High$^\text{row}$, Low$^\text{row}$ in line-wise decomposition and the High$^\text{column}$, Low$^\text{column}$ in column-wise decomposition are calculated using EMD to PAN$^{\text{IMP}}$ image. Then the Low$^\text{column}$, High$^\text{row}$ and High$^\text{column}$ are reconstructed into FI. Finally, a fused multi-spectral image can be gained by IHS inverse transform.

Fig. 3 Seven IMF extracted from panchromatic band image and intensity image

Fig. 4 Multi-spectral band 3,2,1 composite image and panchromatic image

Fig. 5 shows the fusion results using the different models. To compare the fusion effects of the different mode selections, two schemes holding the first and second empirical mode are considered. The fusion result comparison obtained of the two schemes is given in Fig. 6 (only zoom the rectangle region in Fig. 5(d)). Linear edge effect appears because of improper mode selection, especially in the fringe of the point object which is caused by the lack of consideration for the continuity of local 2D space of the EMD 2D extension (row-column extension of 1D EMD).

Therefore, other 2D extension principles can be used for image fusion to gain the best fusion effect with continuity of the fusion image. This will be the future research focus.

The quantitative index value calculated in kinds of evaluation methods is given in Table 1. The information entropy and standard deviation index of the fusion image with the presented method is obviously larger than the original image, but between the wavelet transform fusion and standard IHS fusion. This proves that information of the fusion image is obviously
improved and image definition is well enhanced, which is prior to HIS but low to the improved IHS fusion scheme based on wavelet transform.

The correlation coefficient value obtained with the presented method is higher than the other three schemes, which proved that the method has more priority of holding spectral characteristics of the original image. Additionally, the method has the least spectral distorting index as well as deviation index. All the indexes of the Brovey fusion are worse than the empirical mode fusion scheme except the deviation index. The above analysis suggests that the fusion scheme based on empirical mode decomposition can hold the spectral characteristic and improve image resolution and definition.
Table 1 Quantitative evaluation of the distinct fusion schemes

|                  | Quickbird original image | Improved HIS based on wavelet transform fusion | Brovey fusion | Improved HIS based on EMD |
|------------------|--------------------------|-----------------------------------------------|---------------|--------------------------|
| **Information entropy** |                          |                                               |               |                          |
| Band 1           | 3.84                     | 3.99                                          | 2.77          | 3.92                     |
| Band 2           | 4.65                     | 4.80                                          | 3.64          | 4.73                     |
| Band 3           | 4.48                     | 4.61                                          | 3.35          | 4.54                     |
| **Standard deviation** |                          |                                               |               |                          |
| Band 1           | 17.21                    | 20.30                                         | 17.24         | 18.03                    |
| Band 2           | 37.57                    | 41.01                                         | 38.04         | 38.59                    |
| Band 3           | 29.63                    | 29.60                                         | 9.04          | 30.55                    |
| **Correlation coefficient** |                          |                                               |               |                          |
| Band 1           | 0.84                     | 0.83                                          | 0.86          | 0.94                     |
| Band 2           | 0.88                     | 0.86                                          | 0.81          | 0.96                     |
| Band 3           | 0.88                     | 0.86                                          | 0.84          | 0.95                     |
| **Distorting index** |                          |                                               |               |                          |
| Band 1           | 0.15                     | 0.25                                          | 0.02          | 0.07                     |
| Band 2           | 0.10                     | 0.20                                          | 0.01          | 0.04                     |
| Band 3           | 0.11                     | 0.20                                          | 0.01          | 0.04                     |
| **Torsion resistance** |                          |                                               |               |                          |
| Band 1           | 5.72                     | 6.33                                          | 14.73         | 3.46                     |
| Band 2           | 12.18                    | 14.40                                         | 33.54         | 7.34                     |
| Band 3           | 9.72                     | 11.03                                         | 26.68         | 5.88                     |

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