BEMD based Dimensionality Reduction in Framework for Hyperspectral Image Segmentation

B.Srinivas[1], J.Rajendra Prasad[2]
[1]PP.COMP.SCI.0221,Research Scholar, Department of CS, Rayalaseema University, Kurnool, India.
[2]Professor, Department of IT, PVP Siddhartha, Vijayawada, India.

Abstract: This paper presents dimensionality reduction of hyperspectral dataset using Bi-dimensional Empirical Mode Decomposition (BEMD) in framework for hyperspectral image segmentation using a clustering algorithm. This framework consists of three stages in segmenting a hyperspectral data set. In the first stage, dimensionality reduction algorithm is used, in which the bands that convey less information or redundant data will be removed. In this paper, a methodology based on BEMD is used for selecting k informative bands from d bands dataset. In this method, Band selection is used to seek a band subset preserving most of information from the input data. In proposed method, the Band Correlation measure is used as the measure criterion which can select bands with high classification accuracy and low redundancy. In the second stage, the informative bands which are selected in the second stage are merged into a single image using hierarchical fusion technique. In the hierarchical image fusion, the images are grouped such that each group has equal number of images. After getting fused image, the image is segmented using Fuzzy c-means clustering algorithm. The qualitative and quantitative analysis shows that best informative bands are selected using proposed method which gets high quality segmented image using FCM.
Keywords: Bidimensional empirical Mode Decomposition, Fuzzy C-means, Hypersepctral Imaging

I. INTRODUCTION

The process of acquiring information about an object on the earth using satellites without making any physical contact is called remote sensing [1]. The segmentation of objects on the earth by using electromagnetic radiations reflected or emitted by the surface is the main goal of remote sensing technology. New opportunities to use remote sensing data have arisen, with the increase of spatial and spectral resolution of recently launched satellites. Image segmentation is a key step in remote sensing applications [2]. In remote sensing, sensors are available that can generate hyperspectral data, involving many narrow bands in which each pixel has a continuous reflectance spectrum. Unsupervised image segmentation is an important research topic in hyperspectral imaging, with the aim to develop efficient algorithms that provide high segmentation accuracy [3].

This paper presents a framework for hyperspectral image segmentation using a clustering algorithm. The framework consists of three stages in segmenting a hyperspectral data set. In the first stage, dimensionality reduction algorithm is used to remove the bands that convey less information or redundant data. The dimensionality reduction step decreases many requirements for processing the hyperspectral data set such as storage space, computational load, communication bandwidth etc, thus increasing the efficiency of segmentation algorithm. In the second stage, the informative bands which are selected in the first stage are merged into a single image using hierarchical fusion technique. The main goal of image fusion is to create a single image combining all the features in the selected image bands. After getting a single image, the image is segmented using FCM clustering algorithm. The flow diagram of proposed framework is shown in figure 1. Section 2 presents BEMD based dimensionality reduction method, Section 3 presents Hierarchical Image Fusion, Section 4 presents FCM algorithm for segmentation and Section 5 presents Conclusions.

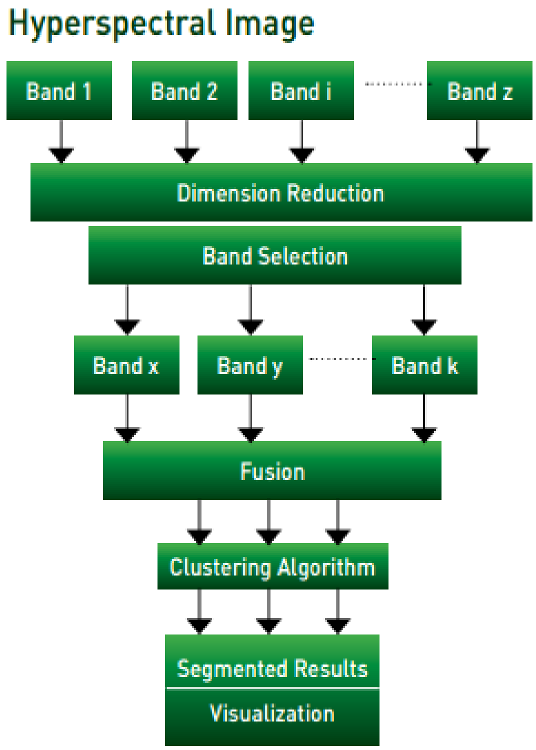


Figure 1: Framework for hyperspectral image segmentation

II. DIMENSIONALITY REDUCTION IN HYPERSPECTRAL IMAGES

Bi-dimensional Empirical Mode Decomposition : Empirical Mode Decomposition [7] is a signal processing method that decomposes any non-linear and non-stationary signal into oscillatory functions called Intrinsic Mode Functions (IMF) and residue. The EMD has the property that the original signal can be reconstructed by combining IMFs and residue. The shifting process [8] to obtain IMFs on a 2-D signal (image) is summarized as follows:

a) Let I(x,y) be a hyperspectral image band. Find all local maxima and local minima points in I(x,y).

b) Interpolate the local maximum points- Upper envelope Up(x,y)

Interpolate the local minimum points- Lower envelope Lw(x,y)

c) Calculate the mean of lower and upper envelopes

$$Mean(x,y) = \frac{(Up(x,y) + Lw(x,y))}{2} \tag{1}$$

d) Subtract the mean of envelopes from original image.

$$Sub(x,y) = I(x,y) - Mean(x,y) \tag{2}$$

e) If Sub(x,y) is an IMF, then

$$IMF_i(x,y) = Sub(x,y) \tag{3}$$

f) Subtract the extracted IMF from the input signal. Now the value of I(x,y) is

$$I(x,y) = I(x,y) - IMF_i(x,y) \tag{4}$$

Repeat steps (b) to (f) for the generating next IMFs.

g) This process is repeated until I(x,y) does not have any local maxima or local minima points. Original hyperspectral image band can be reconstructed given by

$$I(x,y) = \sum_{i=1}^{n} IMF_i(x,y) + res(x,y) \tag{5}$$

Different IMFs reflect different intrinsic information of the input data, and have different features. Band selection is used to seek a band subset preserving most of information from the input data. In this method, the Band Correlation

(BC) is used as the measure criterion which can select bands with high classification accuracy and low redundancy. The BC factor is used to evaluate band subsets. The Band Correlation (BC) can be calculated by:

$$\mathrm{BC}(i,j) = \frac{\sum_{p=1}^{N_b} (x_{ip} - \mu_i) \cdot (x_{jp} - \mu_j)}{\sqrt{\sum_{p=1}^{N_b} (x_{ip} - \mu_i)^2} \cdot \sqrt{\sum_{p=1}^{N_b} (x_{jp} - \mu_j)^2}} \quad (6)$$

The BC factor can be used to estimate the quality of band subsets, firstly we set the band combination B = { }; and we select a band from the input data with the richest information based on entropy as the first selected band. Then we combine each remaining band in the IMF with the selected bands in turn, and the BC of them are calculated. We got the band with the largest BC, and the latest selected band, suppose the band with the largest BC is the ith band in this TIMF, is the ith band in the input data. We repeatedly select band until enough bands are selected and then the finalband subset is obtained, finally we get _ band subsets from the input data based on these IMFs. Considering that different IMFs have different features, we combine these band subsets into a band combination, which contains all intrinsic information of the input data. The block diagram of the proposed band selection method is shown in Fig. 2.

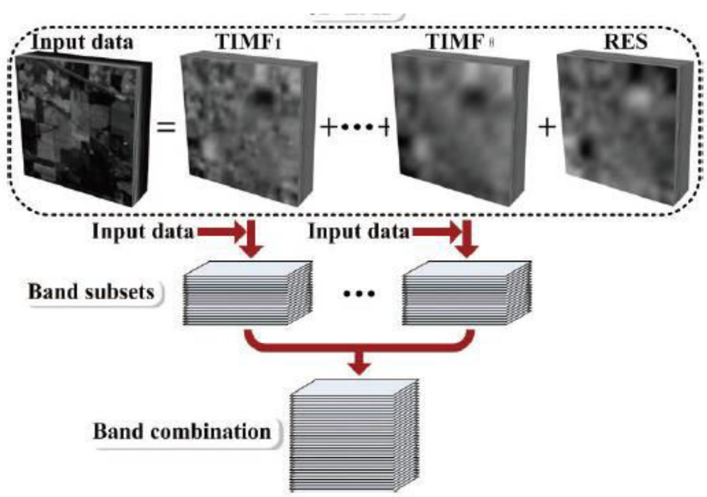


Figure 2: Band Selection using BEMD

III. HIERARCHICAL IMAGE FUSION TECHNIQUE

In hierarchical image fusion technique [8], the entire data set is partitioned into P subsets of hyperspectral, where P is given by P = $\left\lceil \frac{K}{M} \right\rceil$, K number of bands in data set and M bands in each subset. First image fusion is carried out independently on these P subsets, to form P fused images. These P images are used as input for second stage fusion again by dividing into subsets. This procedure is repeated in a hierarchical manner to generate the final result of fusion in a few stages [14]. The flow diagram of hierarchical image fusion is shown in figure 3. The fused image F at any stage is a linear combination of input images as shown below:

$$F(x, y) = \sum_{k=1}^{M} w_k(x, y) I_k(x, y)$$

and

$$\sum_{k=1}^{M} w_i(x, y) = 1, \forall (x, y)$$

wherewk (x, y) is the normalized weight for the pixel at location (x, y), F(x,y) is the fused image [9].

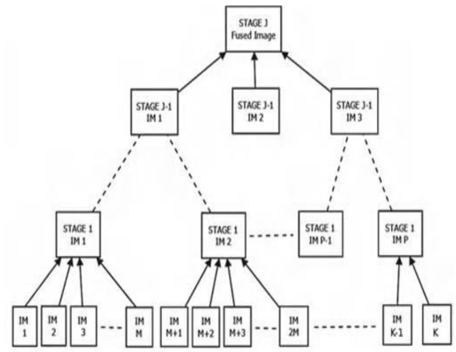


Figure 23: Hierarchical Image Fusion

IV. FUZZY C-MEANS CLUSTERING ALGORITHM

The FCM algorithm for segmentation of hyperspectral image is described below [10]:
Take randomly K initial clusters from the m*n image pixels.
Initialize membership matrix uij with value in range 0 to 1 and value of m=2.
Assign each pixel to the cluster Cj {j=1,2,…..K} if it satisfies the following condition [D(. , .) is the Euclidean distance measure between two values].

$$u_{ij}^{m} D(I_i, C_j) < u_{iq}^{m} D(I_i, C_q), q = 1,2,...,K$$

$$j \neq q$$

The new membership and cluster centroid values as calculated as

$$u_{ik} = \frac{1}{\sum_{j=1}^{K} \left(\frac{D(C_i, I_k)}{D(C_j, I_k)}\right)^{\frac{1}{m-1}}}, for 1 \le i \le K \quad C_j^{\wedge} = \frac{\sum_{j=1}^{n} u_{ij}^{m} I_j}{\sum_{j=1}^{n} u_{ij}^{m}}$$

Continue 2-3 until each pixel is assigned to the maximum membership cluster [11].

V. EXPERIMENTAL RESULTS

The proposed methodology is tested on Pavia University hyperspectral image data set collected from [12] containing 103 spectral bands. The dimensionality reduction is done using proposed BEMD methodology with different similarity metrics and 40 bands selected from 103 bands. After dimensionality reduction, hierarchical image fusion is carried out to create a single image. This image is segmented using Fuzzy c-means clustering algorithm.. The qualitative analysis of the proposed method on Pavia University hyperspectral data set is shown in figure 4. Quantitative analysis using Mean Square Error [13] is a numerically oriented procedure to figure out the performance of algorithm with different similarity metrics used in dimensionality reduction algorithm. The MSE is mathematically defined as:

$$\text{MSE} = \frac{1}{N} \sum_{j=1}^{k} \sum_{i \in c_j} \|vi\text{-}cj\|2$$

Where N is the total number of pixels in an image and vi is the pixel which belongs to the jth cluster [15]. Table 1 shows the quantitative evaluations of three clustering algorithms after segmenting the hyperspectral image. The results confirm that Fuzzy C-means algorithm produces the lowest MSE value for segmenting the hyperspectral image with BEMD based dimensionality reduction algorithm. In future step, the same procedure can be repeated with different clustering algorithms for segmenting the fused hyperspectral image, with different similarity metrics used in dimensionality reduction algorithm.

dimensionality reduction algorithms	MSE Values by FCM algorithm
Entropy	212.8
SAM	192.4
BC	182.6
BEMD + BC	179.8

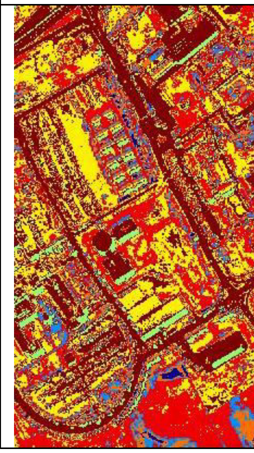
Original image band 100 (Pivia University dataset)	Fused Image	Segmented Image
		

Figure 4: Segmentation of hyperspectral image using FCM

VI. CONCLUSIONS

In this paper a framework for hyperspectral image segmentation is presented. The framework is carried out in three stages. First stage contains dimensionality reduction method using subset selection method to select informative bands leaving the bands that convey less descriptive information, second stage contains hierarchical image fusion to generate a single informative band and in the third stage, segmentation using FCM algorithm. Existing methods for hyperspectral data sets is done by selecting limited number of bands normally less than seven. The accuracy of any segmentation algorithm decreases if the number of spectral bands increases. The framework presented in this paper provides a methodology for segmenting the hyperspectral data set by incorporating all the information existing in the original bands rather than selecting some spectral bands. The methodology presented in this paper shows the performance of FCM algorithm by using different similarity metrics in dimensionality reduction algorithm.

VII. REFERENCES

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