Indonesian Journal of Electrical Engineering and Computer Science
Vol. 3, No. 3, September 2016, pp. 503 ~ 511
DOI: 10.11591/ijeecs.v3.i2.pp503-511

Dimensionality Reduction and Classification of Hyperspectral Images using Genetic Algorithm

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Abstract

This paper presents genetic algorithm based band selection and classification on hyperspectral image data set. Hyperspectral remote sensors collect image data for a large number of narrow, adjacent spectral bands. Every pixel in hyperspectral image involves a continuous spectrum that is used to classify the objects with great detail and precision. In this paper, first filtering based on 2-D Empirical mode decomposition method is used to remove any noisy components in each band of the hyperspectral data. After filtering, band selection is done using genetic algorithm in-order to remove bands that convey less information. This dimensionality reduction minimizes many requirements such as storage space, computational load, communication bandwidth etc which is imposed on the unsupervised classification algorithms. Next image fusion is performed on the selected hyperspectral bands to selectively merge the maximum possible features from the selected images to form a single image. This fused image is classified using genetic algorithm. Three different indices, such as K-means Index (KMI) and Jm measure are used as objective functions. This method increases classification accuracy and performance of hyperspectral image than without dimensionality reduction.

Keywords: *image classification, empirical mode decomposition, genetic algorithm, hyperspectral image.*

1. 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 classification of objects on the earth by using electromagnetic radiations reflected or emitted by the surface is the main goal of remote sensing technology [2]. New opportunities to use remote sensing data have arisen, with the increase of spatial and spectral resolution of recently launched satellites. Image classification is a key step in remote sensing applications [3]. 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 classification is an important research topic in hyperspectral imaging, with the aim to develop efficient algorithms that provide high classification accuracy.

The hyperspectral images suffer from noises due to disturbance of transmission medium in the atmosphere or degradation of sensors etc leading to affect the accuracy of classification algorithms. This paper presents hyperspectral image classification using EMD and Image fusion. 2-D Empirical mode decomposition method is used to divide the hyperspectral image belonging to a specific band into finite number of components called intrinsic mode functions. The last component is called a residue. The first IMF is filtered using median filter. The summation of filtered IMF and remaining IMFs plus residue gives the de-noised image. The same procedure is repeated for all the bands. After filtering band selection is done using genetic algorithm. The selected bands are fused into a single image for application oriented visualization, effective interpretation, extraction of useful features, and to provide a better description of the scene using reduced data sets. After fusion, the image is classified using genetic algorithm with three different objective functions. This method increases the classification accuracy both in qualitative and quantitative analysis.

This paper is structured as follows: section 2 presents filtering using bi-dimensional empirical mode decomposition, section 3 presents genetic algorithm mechanism, section 4

Received April 2, 2016; Revised July 25, 2016; Accepted August 10, 2016

presents band selection using genetic algorithm, section 5 presents image fusion technique, section 6 presents image classification using genetic algorithm, section 7 shows experimental results and section 8 report conclusions.

2. Empirical Mode Decomposition

Empirical mode decomposition [4] is a signal processing method that nondestructively fragments any non-linear and non-stationary signal into oscillatory functions by means of a mechanism called shifting process. These oscillatory functions are called Intrinsic Mode Functions (IMF), and each IMF satisfies two properties, (a) the number of zero crossings and extrema points should be equal or differ by one. (b) Symmetric envelopes (zero mean) interpret by local maxima and minima [5]. The signal after decomposition using EMD is non-destructive means that the original signal can be obtained by adding the IMFs and residue. The first IMF is a high frequency component and the subsequent IMFs contain from next high frequency to the low frequency components. The shifting process [6] used to obtain IMFs on a 2-D signal (image) is summarized as follows:

a) Let I(x,y) be a Remote Sensing Image used for EMD decomposition. Find all local maxima and local minima points in I(x,y).
b) Upper envelope Up(x,y) is created by interpolating the maxima points and lower envelope Lw(x,y) is created by interpolating minima points. This interpolation is carried out using cubic spline interpolation method.
c) Compute the mean of lower and upper envelopes denoted by Mean(x,y).

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

d) This mean signal is subtracted from the input signal.

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

e) If Sub(x,y) satisfies the IMF properties, then an IMF is obtained.

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

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 the above steps (b) to (f) for the generation of next IMFs.

g) This process is repeated until I(x,y) does not have maxima or minima points to create envelopes.

Original Image can be reconstructed by inverse EMD given by:

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

Image Denoising using EMD:

The mechanism of de-noising using EMD is summarized as follows:

a) Apply 2-D EMD for each band in the hyper spectral image to obtain IMFi (i=1, 2, …k). The k^{th} IMF is called residue.
b) The first intrinsic mode function (IMF1) contains high frequency components and it is suitable for denoising. This IMF1 is denoised with This IMF1 is de-noised with median filter. This de-noised IMF1 is represented with DNIMF1.
c) The new band is reconstructed by the summation of FIMF and remaining IMFs given by

$$RI = DNIMF1 + \sum_{i=2}^{k} IMF_i \quad (6)$$

Where RI is the reconstructed band.

3. Genetic Algorithm

Genetic Algorithms [7] belong to the class of evolutionary algorithms that are based on principles of natural selection and genetics. It is a search technique used in computing true solutions to optimization problems that is driven by natural evolution process. GA performs parallel search of the solution space rather than point by point search. Genetic Algorithm consists of three operators namely, Selection, Crossover and Mutation.

The Genetic Algorithm mechanism can be abstracted as follows [8].

1) The initial population of solutions is randomly generated across the search space.
2) Using an objective function, the fitness of each individual solution in the population is evaluated.
3) Using this fitness values, the solutions in the population are selected.
4) New population is created from selected solutions using the crossover and mutation operators.
5) The new population is replaced instead of old population.
6) Repeat iteratively from (2) to (5) until a stop criterion is satisfied. Each iteration of this GA process is called generation.

GA is a method of parallel search of the solution space based on two assumptions inspired by evolutionary biology. 1) The measure of problem solving ability by an individual in the population is determined by its fitness value. 2) New individuals which are obtained by combining different individuals in the population have more problem solving ability.

4. Band Selection Technique using Genetic Algorithm

Hyperspectral image bands are the result of sampling a continuous spectrum at narrow wavelength intervals where the nominal bandwidth of a single band is 10 nm [9]. The spectral response of the scene varies gradually over the spectrum, and thus, the successive bands in the hyperspectral image have a significant correlation. The dimensionality of the hyperspectral data set strongly affects the performance of any unsupervised classification algorithm. Some of the bands contain redundant data and some contain less discriminatory information between others. In-order to process this high dimensional data, many requirements such as storage space, computational load, communication bandwidth etc is imposed on the classification algorithm. Therefore it is advantageous to remove bands that convey less information. The band selection is done according to any of these following metrics.

Euclidean Distance (ED) [9]: It is vector distance measurement between any two vectors, defined as:

$$ED(X,Y) = \sqrt{\sum_{k=1}^{N} (X_k - Y_k)^2} \quad (7)$$

Where X and Y are two vectors and N_b denotes the number of bands.

Spectral Angle Mapper (SAM) [10]: It is a vector angle measurement between any two vectors, defined as:

$$SAM(X,Y) = \arccos\left(\frac{X^T.Y}{\|X\|.\|Y\|}\right) \quad (8)$$

Where X and Y are two vectors and Nb denotes the number of bands.

Spectral Correlation Mapper (SCM) [11]: It is a vector correlation measure that measures the strength of the linear relationship between two vectors, defined as:

$$\mathrm{SCM}(X,Y) = \frac{\sum_{k=1}^{N_b} (X_k - \mu_X) \cdot (Y_k - \mu_Y)}{(N_b - 1) \cdot \sigma_X \cdot \sigma_Y} \tag{9}$$

Where X and Y are two N_b dimensional spectral vectors and μ denotes the mean and σ denotes the standard deviation of corresponding vector.

Band Correlation (BC) [12]: It is statically based vector correlation measurement that indicates the information redundancy of each spectral band. The band correlation is defined as:

$$\mathrm{BC}(i,j) = \frac{\sum_{p=1}^{N_b} (x_{ip} - \mu_i) \cdot (x_{jp} - \mu_j)}{\sqrt{\sum_{p=1}^{N_b} (x_{ip} - \mu_i)^2} \cdot \sqrt{\sum_{p=1}^{N_b} (x_{jp} - \mu_j)^2}} \tag{10}$$

Where BC(i,j) is th correlation coefficients of bands i and j, x_{ip} and x_{jp} are the pixel value of bands i and j, respectively and μ_i and μ_j represent the mean of bands I and j, respectively. For ED and SAM bands with larger values are selected and for SCM and BC bands with smaller values are selected.

The genetic algorithm for band selection is described as follows:

a) Assume P chromosomes in the population where P is the size of the population. Each chromosome is a string of zeros and ones; the string length is equal to the number of bands in the data set. Zero bits in the string denote the corresponding band is not selected and one denotes the selection of specific band. In this method, we assume the total number of selected bands is fixed i.e., the total number of ones in each chromosome is fixed.
b) Using an objective function, the fitness value of each chromosome is evaluated. The fitness function is defined as:

$$fitnessfunction = \frac{SCM * BC}{ED * SAM} \tag{11}$$

c) The selection of chromosomes is done based on the fitness value using roulette wheel technique.
d) By applying single point crossover and mutation operators, a new population is produced from the parents. This new population replaces the old population. At any iteration the number of selected bands in each chromosome is fixed.
e) Maximum number of iterations is used as stopping criteria.

After the execution stops, the highest fitness value chromosome is selected and the values in this chromosome represent the solution to the band selection.

5. Image Fusion Technique

The hyperspectral data present abundant multidimensional information that contains far more image bands than those that can be displayed on the standard tristimulus display. Therefore, an efficient and appropriate means of visualization of the hyperspectral data is needed [13].

Let us consider I_1, I_2, …. I_k be a set of hyperspectral bands, containing K selected bands. We want to fuse these bands to generate a high contrast resultant image for visualization. The primary aim of image fusion is to selectively merge the maximum possible features from the selected images to form a single image. Therefore, for an efficient fusion, we should be able to extract the specific information contained in a particular band [14].

The fused image F at each stage can be represented as a linear combination of input images I_k, k = 1 to M as shown below:

$$F(x,y)=\sum_{k=1}^{M} w_k(x,y) I_k(x,y)$$
$$and \tag{12}$$
$$\sum_{k=1}^{M} w_i(x,y)=1, \forall (x,y)$$

Where w_k (x, y) is the weight for the pixel at location (x, y) in the k-th observation and F(x,y) is the fused image. The weights are directly proportional to the finer details in the hyperspectral band. We calculate the weights required of fusion according to the given formula.

$$w_k(x,y)=\frac{|I_k(x,y)-I_k^{\mathrm{BF}}(x,y)|}{\sum_{k=1}^{K}(|I_k(x,y)-I_k^{\mathrm{BF}}(x,y)| \qquad)} \tag{13}$$

Where k denotes the band number and IBF denoted the image that is obtained using bilateral filter.

The bilateral filtering operation is defined as follows:

$$I^{\mathrm{BF}}(x,y)=\frac{1}{W(x,y)}\sum_{\tilde{x}}\sum_{\tilde{y}}\left\{G_{\sigma_S}(x-\tilde{x},y-\tilde{y})\, G_{\sigma_R}\left(I(x,y)-I(\tilde{x},\tilde{y})\right) I(\tilde{x},\tilde{y})\right\}$$
$$G_{\sigma_S}(x,y)=\exp\left(-\frac{x^2+y^2}{2\sigma_S^2}\right)$$
$$G_{\sigma_R}(\zeta)=\exp\left(-\frac{\zeta^2}{2\sigma_R^2}\right)$$
$$W(x,y)=\sum_{\tilde{x}}\sum_{\tilde{y}}\left\{G_{\sigma_S}(x-\tilde{x},y-\tilde{y})\, G_{\sigma_R}\left(I(x,y)-I(\tilde{x},\tilde{y})\right)\right\}, \tag{14}$$

Where GσS be the Gaussian spatial kernel, GσR be the Gaussian range kernel , σR decides the amplitude of the edge and its corresponding weight, (˜x, ˜y) is the neighborhood corresponding pixel, W(x, y) is the normalization factor and IBF(x,y) is the output bilateral filtered image.

6. Image Classification Using Genetic Algorithm

The Genetic Algorithm is applied as follows.

a) Assume P chromosomes in the population where P is the size of the population. Each chromosome is encoded with K cluster centers that are randomly selected from the image.
b) Using an objective function, the fitness value of each chromosome is evaluated. Two Different indices, such as K-means index (KMI) and Jm measure are used as objective functions individually. For computing the measures, the centers z_1, z_2, …., z_k encoded in a chromosome are first extracted. The membership values u_{ik}, i=1,2,….K and k=1,2,….n are computed [15] as follows:

$$u_{ik}=\frac{1}{\sum_{j=1}^{K}\left(\frac{D(z_i,x_k)}{D(z_j,x_k)}\right)^{\frac{2}{m-1}}} \tag{15}$$

Where $D(z_i,x_k)$ is the Euclidean distance between two points x_k and cluster center z_i.

The centers encoded in a chromosome are updated using the following equation:

$$z_i = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}, \qquad 1 \le i \le K \tag{16}$$

The J_m measure [16] which is to be minimized is defined as

$$J_m = \sum_{j=1}^{n}\sum_{k=1}^{K} u_{kj}^m D^2(x_j, z_k), \qquad 1 \le m \le \infty \tag{17}$$

Where m is the fuzzy exponent, D denotes the Euclidean distance between two points x_j and z_k and u_{kj} denotes the membership values.

The k-means index [17] [19] which is used as the objective function in this GA process is defined as follows:

$$KMI = \frac{1}{\sum_{k=1}^{K}\sum_{i=1}^{N}\left\|x_i - z_k\right\|^2} \tag{18}$$

Where K number of clusters and z_k is the cluster centers

c) The selection of chromosomes is done based on the fitness value using roulette wheel technique.
d) By applying crossover and mutation operators with rate 0.8 and 0.07, a new population is produced from the parents. This new population replaces the old population.
e) Maximum number of iterations is used as stopping criteria.

After the execution stops, the highest fitness value chromosome is selected and the values in this chromosome represent the solution to the classification of image.

5. Experimental Results

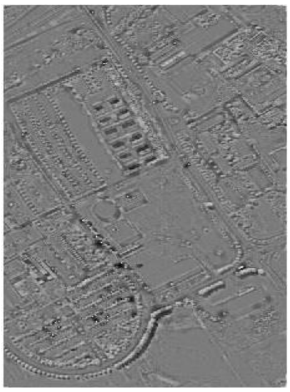
The proposed methodology is tested on Pavia University and Indian pines hyperspectral image data set. The Pavia University data set contains 103 spectral bands and image in each band consists of 610*340 pixels. The Indian Pines data set contains 200 spectral bands and image in each band consists of 145*145 pixels. The data sets are collected from [18] that consist of nine classes in Pavia university data set and sixteen classes in Indian Pines data set with the geometric resolution is 1.3 meters. The filtering using BEMD is conducted on band 100 in each of the data set and is shown in Figure 1. The same procedure is executed for all bands in the data set in-order to enhance the image. The band selection is done using genetic algorithm. From the two data sets 50 best bands are selected. The qualitative analysis of the proposed method on Pavia University and Indian Pines hyperspectral data set is shown in Figure 1. Table 1 specifies the quantitative index values of the proposed method compared with the ground truth information available in [18].

Table 1. Classification Accuracy of Proposed Method on Two Different Data Sets

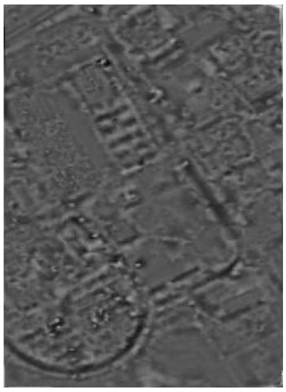
	Pavia University		Indiana Pines	
Objective Function	CA%	Kappa Coefficient	CA%	Kappa Coefficient
KMI	78.51	0.741	77.6	0.732
Jm	89.21	0.831	88.4	0.862

Pavia University image band 100

IMF1



IMF2



IMF3

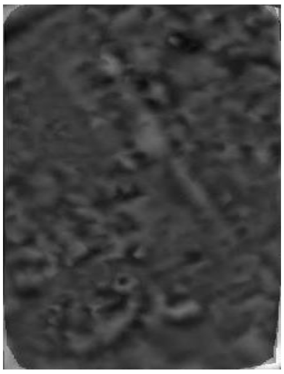
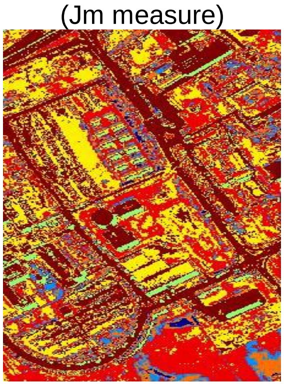


Image Band after de-noising using IMF and Median filter

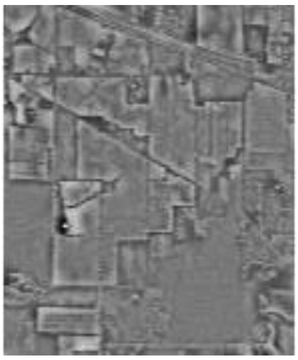
Fused Image after band selection

Classified Using GA (Jm measure)



Indian pines data set- image band 100

IMF1



IMF2

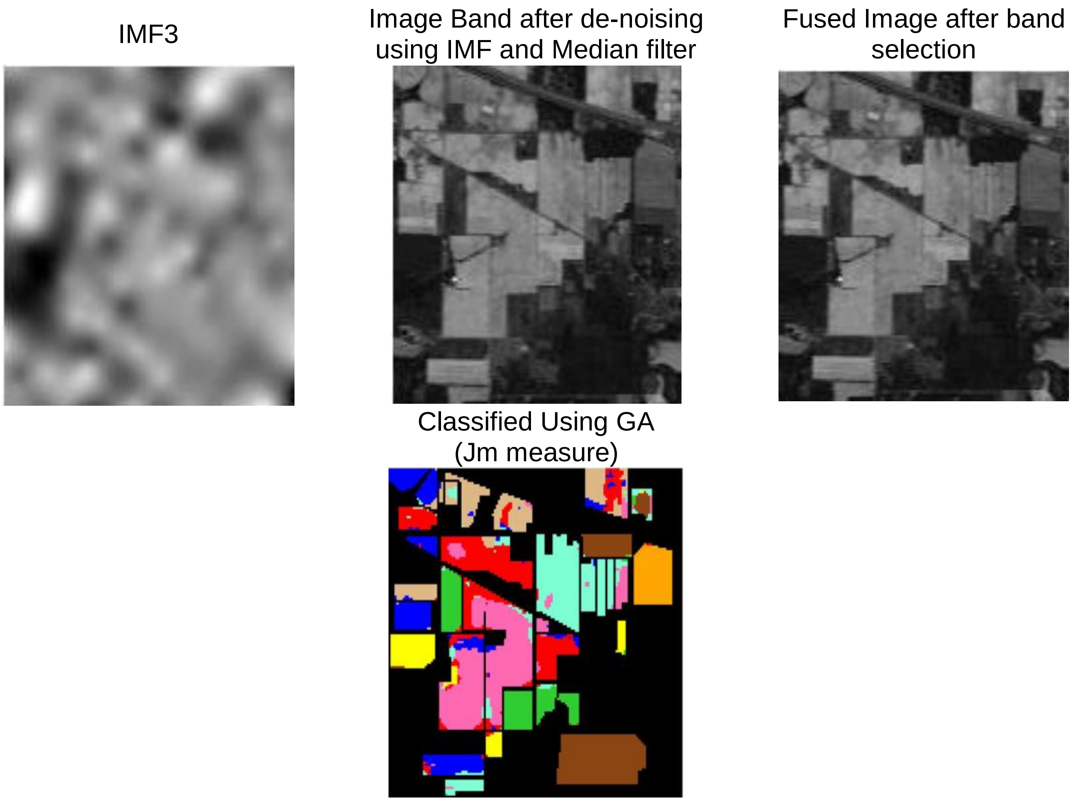


Figure 1. Hyperspectral Image classification

7. Conclusions

In this paper, hyperspectral band selection and classification using genetic algorithm is presented. EMD is used in the preprocessing stage for removal of noise in hyperspectral bands. After noise removal, the dimensionality of the data set is reduced using band selection algorithm. The algorithm removes the bands in the data set that convey less information for classification. The selected bands are fused into a single image for visualization purpose. This fused image is classified using Genetic algorithm with two different objective functions. The experimental results show that Jm index as objective function in GA classifies the hyperspectral image more efficiently.

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