Indonesian Journal of Electrical Engineering and Computer Science
Vol. 2, No. 3, June 2016, pp. 703 ~ 711
DOI: 10.11591/ijeecs.v2.i3.pp703-711

Image Fusion in Hyperspectral Image Classification using Genetic Algorithm

B Saichandana*[1], K Srinivas[2], R Kiran Kumar[3]
[1]Department of CSE, JNTU Kakinada
[2]Department of CSE, VR Siddhartha Engineering College, Vijayawada
[3]Department of CS, Krishna University, Machilipatnam
*Corresponding author, email: bschandana@gmail.com

Abstract

Hyper spectral 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. This paper presents hyperspectral image classification mechanism using genetic algorithm with empirical mode decomposition and image fusion used in preprocessing stage. 2-D Empirical mode decomposition method is used to remove any noisy components in each band of the hyperspectral data. After filtering, image fusion is performed on the hyperspectral bands to selectively merge the maximum possible features from the source images to form a single image. This fused image is classified using genetic algorithm. Different indices, such as K-means (KMI), Davies-Bouldin Index (DBI), and Xie-Beni Index (XBI) are used as objective functions. This method increases classification accuracy of hyperspectral image.

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 [19]. 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 wavelets shrinkage denoising method. 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 the 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 image fusion technique, section 4 presents Genetic algorithm for image classification, section 5 shows experimental results and section 6 report conclusions.

Received March 17, 2016; Revised April 29, 2016; Accepted May 14, 2016

2. Empirical Mode Decomposition

Empirical mode decomposition [5] 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 [6]. 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 [7] [12] 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 wavelet shrinkage denoising method presented in [18]. This de-noised IMF1 is represented with DNIMF1.
c) The new band is reconstructed by the summation of FIMF and remaining IMFs given by

$$RI = DNIMF1 + \sum_{i=2}^{k} IMF_i \tag{6}$$

Where RI is the reconstructed band.

3. 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 [8].

Let us consider I_1, I_2, …. I_k be a set of hyperspectral bands, containing K consecutive 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 source images to form a single image. 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. Therefore, for an efficient fusion, we should be able to extract the specific information contained in a particular band [13].

The process of combining a few hundred bands into a single image may involve reading all the bands in the input hyperspectral image at once, computing the weights, and generating a resultant fused image as the linear combination of all the input bands. This one time reading and combining all the image bands have the following shortcomings [8].

1. Fractional Weights: This results in assigning very small fractional weights to the locations in each of the image bands that might lead to washing out some of the minor details.
2. Memory requirements: As the size of hyperspectral data is very large, it requires huge amount of memory to read the data and merge.

In order to overcome these issues, a hierarchical method for image fusion is used for hyperspectral data. Instead of fusing the entire set of bands at a single time, this method creates partitions of the data into subsets of hyperspectral bands. For a given image of dimensions (X × Y × K), containing K bands, form P subsets of dimensions (X × Y × M) from contiguous bands of the data, where P is given by P = $\left\lceil \frac{K}{M} \right\rceil$.

The first stage image fusion scheme may be employed to each of these subsets independently to obtain P fused images. These P images form the base images (or inputs) for the second-stage fusion. This procedure is repeated in a hierarchical manner to generate the final result of fusion in a few stages. The same process continues till the single fused image which represents the combining of the entire data is generated. Figure 2 shows the schematic of the hierarchical scheme of fusion. 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:

$$F(x,y) = \sum_{k=1}^{M} w_k(x,y) I_k(x,y)$$
$$and \tag{7}$$
$$\sum_{k=1}^{M} w_i(x,y) = 1, \forall (x,y)$$

where w_k (x, y) is the weight for the pixel at location (x, y) in the k-th observation, F(x,y) is the fused image and the sum of all weights at any spatial location equals unity, i.e., normalized weights.

4. Genetic Algorithm

Genetic Algorithms [14] 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 [15].
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.

Image Classification using GA

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. Three Different indices, such as K-means index (KMI) [16], Jm measure and Xie-Beni Index (XBI) [17] 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 [10] as follows:

$$u_{ik} = \frac{1}{\sum_{j=1}^{K} \left(\frac{D(z_i, x_k)}{D(z_j, x_k)} \right)^{\frac{2}{m-1}}} \tag{8}$$

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:

$$z_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}, \qquad 1 \le i \le K \tag{9}$$

The XB index is defined as the function of ration of the total variation to the minimum separation of the clusters, which is given by the following equation

$$\mathrm{XB} = \frac{\sigma(U, Z; X)}{n\,\mathrm{sep}(Z)} = \frac{\sum_{i=1}^{K} \left(\sum_{k=1}^{n} u_{ik}^2 D^2(z_i, x_k) \right)}{n \left(\min_{i \neq j} \{ D^2(z_i, z_j) \} \right)}. \tag{10}$$

The J_m measure [18] which is to be minimized is defined as

$$J_m = \sum_{j=1}^{n} \sum_{k=1}^{K} u_{kj}^m D^2(x_j, z_k), \qquad 1 \le m \le \infty \tag{11}$$

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] which is used as the objective function in this GA process is defined as follows:

$$KMI = \frac{1}{\sum_{k=1}^{K}\sum_{i=1}^{N}\left\| x_i - z_k \right\|^2} \tag{12}$$

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 [11] 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 experimental result 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 and finally increase the classification accuracy. 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 [11].

Table 1. Classification accuracy of proposed method on two different data sets

Pavia University	Without EMD		With EMD	
Objective Function	CA%	Kappa Coefficient	CA%	Kappa Coefficient
KMI	74.51	0.682	79.3	0.742
Jm	84.21	0.829	89.4	0.823
XB	88.52	0.852	94.32	0.904

Indian Pines	Without EMD		With EMD	
Objective Function	CA%	Kappa Coefficient	CA%	Kappa Coefficient
KMI	69.41	0.682	74.3	0.713
Jm	81.62	0.799	88.4	0.813
XB	84.62	0.842	93.9	0.894

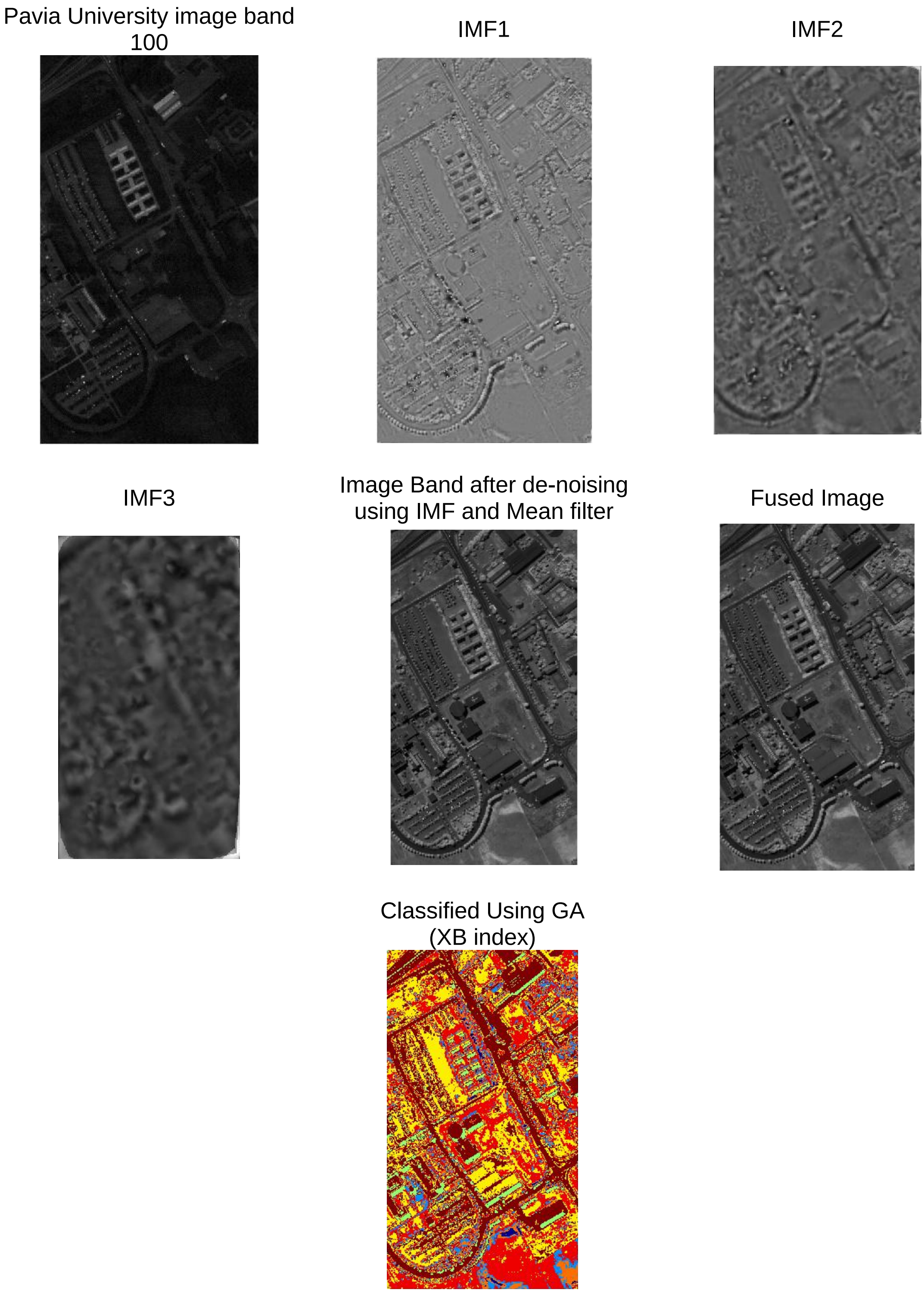

Figure 1. Hyperspectral Image classification (*cont.*)

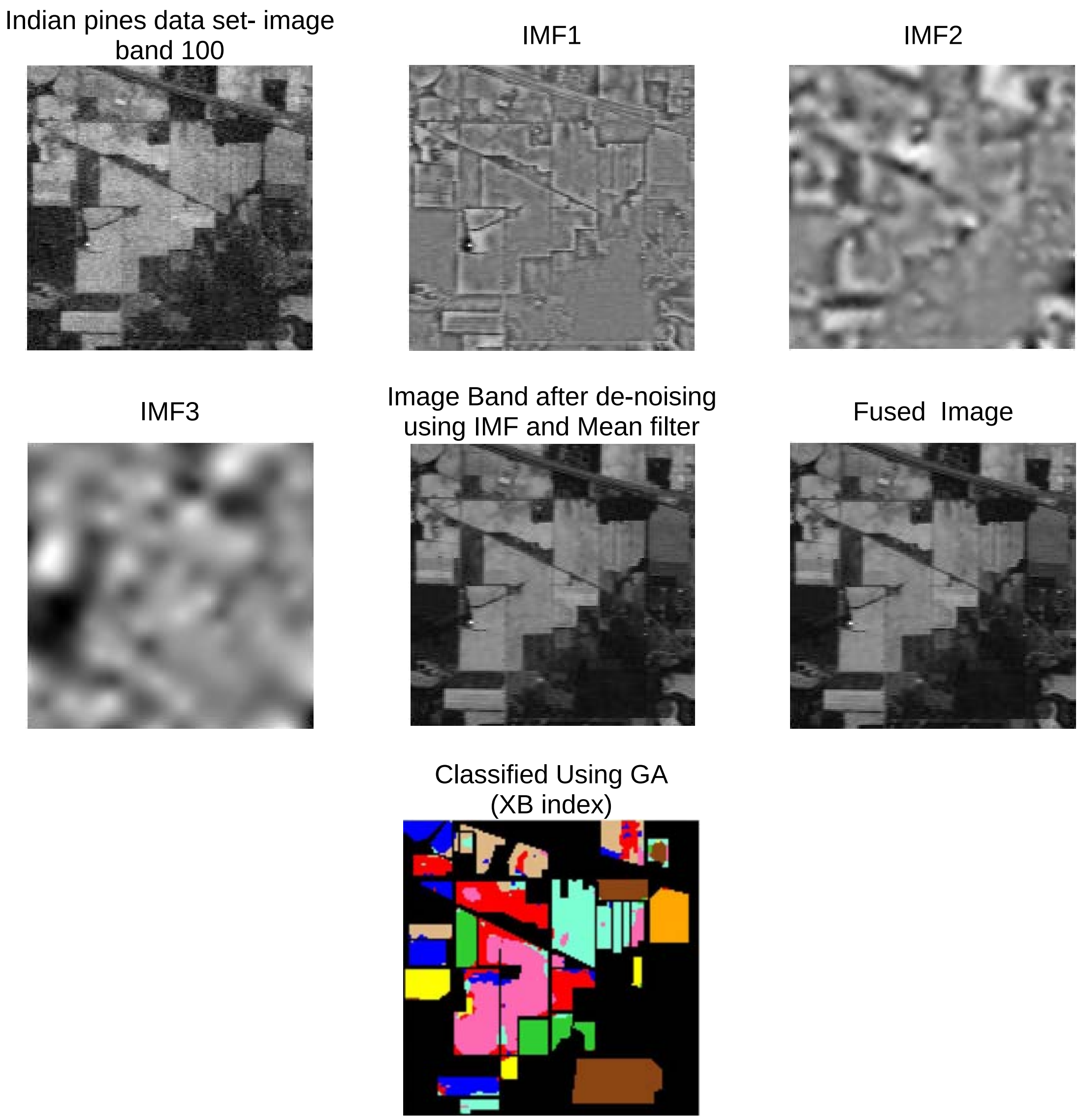

Figure 1. Hyperspectral Image classification

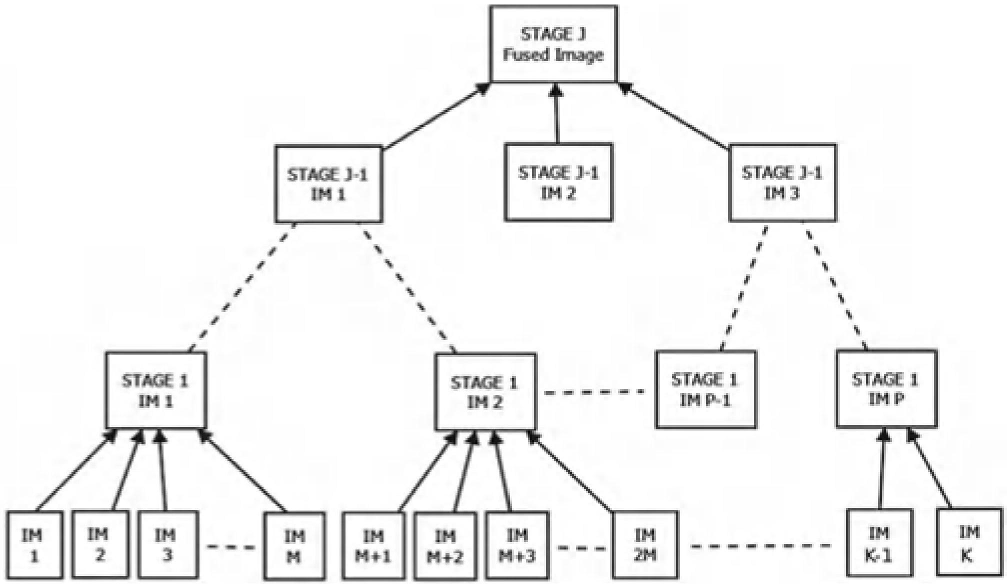

Figure 2. Hierarchical Scheme of Image Fusion

7. Conclusions

In this paper, hyperspectral image classification based on EMD and Image fusion is presented. EMD is used in the preprocessing stage for removal of noise in hyperspectral bands. After noise removal, the image bands are fused into a single image for visualization purpose. This fused image is classified using Genetic algorithm with three different objective functions. The experimental results show that XB index as objective function in GA classifies the hyperspectral image more efficiently. The EMD filtering mechanism increases the accuracy of classification algorithm.

References

[1] Yi Ma, Jie Zhang and Yufeng Gao. "*High Resolution Remote Sensing Image Classification of Coastal Zone and its Automatic Realization*". Proceedings of IEEE International Conference on Computer Science and Software Engineering. 2008: 827-829.

[2] Xiaofang Liu et.al. "*Remote Sensing Image Classification Using Function Weighted FCM Clustering Algorithm*". Proceedings of IEEE International Geosciences and Remote Sensing Symposium. 2007: 2010-2013.

[3] Nor Ashidi Mat Isa, Samy A.Salamah, Umi Kalthum Ngah. "Adaptive Fuzzy Moving K-means Clustering Algorithm for Image Segmentation". *IEEE Transactions on Consumer Electronics*. 2012; 55(4): 2145-2153.

[4] Siti Naraini Sulaiman, Nor Ashidi Mat Isa. "Denoising based Clutering Algorithms for Segmentation of Low level of Salt and Pepper Noise Corrupted Images". *IEEE Transactions on Consumer Electronics*. 2010; 56(4).

[5] JC Nunes et al. "Image analysis by bidimensional empirical mode decomposition". *Image Video Computing.* 2003; 21(12): 1019–1026.

[6] Zeiler A, et.al. "*Empirical Mode Decomposition- an Introduction*". in Proceedings of IEEE International Joint Conference on Neural Networks. 2010: 1-8.

[7] Alp Erturk, et.al. "Hyperspectral Image Classification Using Empirical Mode Decomposition with Spectral Gradient enhancement". *IEEE Transactions on GEoscience and RemoteSensing*. 2013; 51(5): 2787-2790.

[8] Ketan Kotwal, et al. "Visualization of Hyperspectral Images Using Bilateral Filtering". *IEEE transactions of Geoscience and remote Sensing*. 2010; 48(5): 2308-2319.

[9] B Guo, S Gunn, B Damper and J Nelson. "*Hyperspectral image fusion using spectrally weighted kernels*". in Proc. 8th Int. Conf. Inf. Fusion, Philadelphia, PA. 2005; 1: 402–408.

[10] J Harikiran, et al. Multiple Feature Fuzzy C-means clustering algorithm for segmentation of microarray image". *Internatonal journal of Electrical and Computer Engineering*. 2015; 5: 1045-1053.

[11] http://www.ehu.eus/ccwintco/index.php?title=Hyperspectral_Remote_Sensing_Scenes.

[12] B Saichandana et al. "Clustering Algorithm Combined with Empirical Mode Decomposition for Classification of Remote Sensing Image". *IJSER.* 2014; 5(9): 686-695.
[13] Subhasis Chaudhuri, Ketan Kotwal. "Hyperspectral Image Fusion". Springer book.
[14] J Holland. "Adaptation in Natural and Artificial Systems". Ann Arbor, MI: Univ. of Michigan Press. 1975.
[15] A Erturk et al. "Hyper Spectral Image Classification Using Empirical Mode Decomposition with Spectral Gradient enhancement". *IEEE Transactions on Geoscience and Remote Sensing*. 51(5): 2787-2798.
[16] B Sanghamitra et al. "Multiobjective Genetic Clustering for Pixel Classification in Remote Sensing Imagery". *IEEE Transactions on Geoscience and Remote Sensing*. 2007; 45(5): 1506-1512.
[17] Yeh Fen, Yang et al. "Genetic Algorithms for Multispectral Image Classification". http://www.isprs.org/proceedings/XXXVI/part3/singlepapers/P_16.pdf.
[18] Anutam and Rajni. "Performance Analysis of Image Denoising with Wavelet Thresholding Methods for different Levels of Decomposition". *The International Journal of Multimedia and its applications*. 2014; 6(3): 35-46.
[19] B Saichandan et al. "Clustering Algorithm Combined with Hill Climbing for Classification of Remote Sensing Image". *International Journal of Electrical and Computer Engineering*. 2014; 4(6): 923-930.