Hyperspectral Image Classification Using ANN Classfier

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Abstract-- Hyperspectral imagery provides the potential for more accurate and detailed information extraction than possible with any other type of remote sensed data. Therefore precise classification of hyperspectral images plays a vital role in many practical applications. In this project, a new method of dimension reduction for hyperspectral image analysis by using laplacian eigen values, is proposed.

Hyperspectral image considered is pre-processed which includes resizing, de-noising and color separation. The resulting image is segmented using K-means algorithm. Spectral-spatial features are extracted from the segmented image. Laplacian Eigen values are generated for the extracted features. Then, feature vectors are created using the generated Laplacian eigen values. Then classification is done using ANN classifier to generate knowledge base. In hyperspectral image four types of regions, also considered as four classes are identified. The four different regions being identified are mountains, forest areas, land regions and water bodies. This constitutes the training phase. In the testing stage, the geographical regions in the hyperspectral image which is to be tested is classified using ANN classifier. Statistical data is obtained for proper image analysis. Experimental results show that the proposed method is effective for classification of the type of geographical region in the hyperspectral image.

Keywords-*Hyperspectral image, K-means, Spectral-spatial, ANN*

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1. Introduction

Hyperspectral image is a set of data which measure the spectrum of solar radiation reflected by the earth's surface [1]. These images have many applications in meteorology, agriculture, geology, forestry, landscape, biodiversity conservation, regional planning, education, intelligence and warfare. The information contained in hyperspectral image allows the characterization, identification, and classification of the land-covers with improved accuracy and robustness. With very narrow spectrum band, hyperspectral image data include ample information, which reflects tiny differences among materials of the earth's surface. Hyperspectral image is of high input dimension of pixels, small number of labelled samples, and spatial variability of the spectral signature.

The proposed system deals with the classification of Hyperspectral image efficiently. ANN has been used in hyperspectral image classification and has achieved performance competitive with the best available algorithm. The technique for the spectral-spatial classification of hyperspectral images often consist of three steps: choosing the limited training samples, extracting the spectral-spatial features and designing an ANN classifier. The whole process takes place in two stages: Training stage and Testing stage.

Firstly, Hyperspectral image considered is pre-processed which includes resizing, de-noising and color separation. The resulting image is segmented using K-means algorithm. Spectral-spatial features are extracted from the segmented image. Laplacian Eigen values are generated for the extracted features. Then, feature vectors are created using the generated Laplacian eigen values. Then classification is done using ANN classifier to generate knowledge base. This constitutes the training phase. In the testing stage the Hyperspectral image which is to be tested is classified using ANN classifier to obtain the statistical data for proper image analysis.

2. Methodology

The methodology of our work is represented in the form of block diagram as displayed in Figure 1.

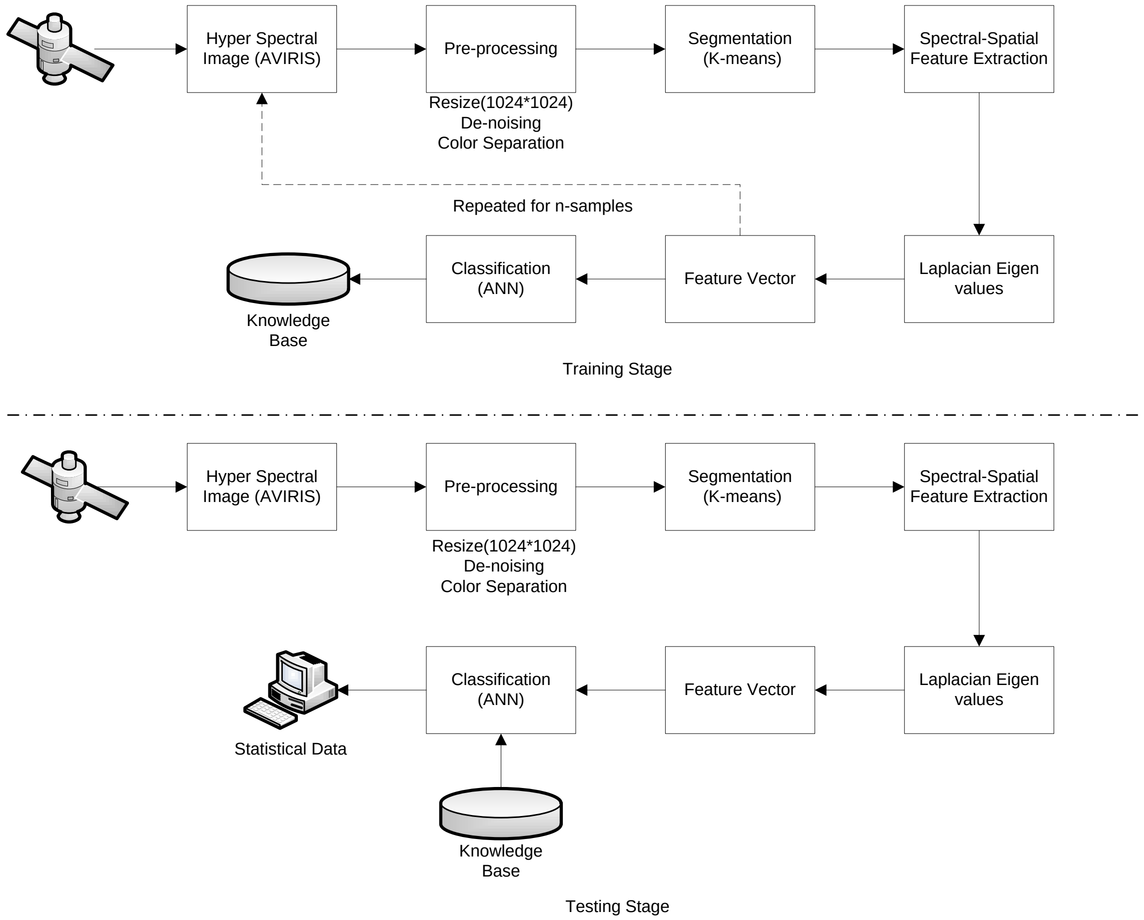


Figure 1: Block Diagram of the Proposed System

A.Segmentation

The main idea of the image segmentation is to group pixels (super pixels) in homogeneous regions and the usual approach to do this is by ‘common feature. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic.
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center.
3. Re-compute the cluster centres by averaging all of the pixels in the cluster.
4. Repeat steps 2 and 3 until convergence is attained.

let a set of observations (**x**1, **x**2, …, **x***n*), where each observation is a *d*-dimensional real vector, *k*-means clustering aims to partition the *n* observations into *k* sets ($k \leq n$) **S** = {*S*1, *S*2, …, *Sk*} so as to minimize the within-cluster sum of squares (WCSS):

$$arg_s min \sum_{i=0}^{k} \sum_{x_j \in s_i} \left\| x_j - \mu_i \right\|^2$$

where μ_i is the mean of points in *Si*

Given an initial set of *k* means $m1^{(1)},\ldots,mk^{(1)}$,the algorithm proceeds by alternating between two steps:

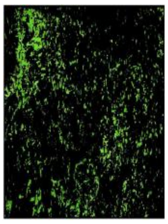
$$S_i^{(t)}=\left\{ \boldsymbol{Xp}: \left\| \boldsymbol{Xp} - \boldsymbol{mi}^{(t)} \right\|^2 \leq \left\| \boldsymbol{Xp} - \boldsymbol{mj}^{(t)} \right\|^2 \forall \boldsymbol{j},\ \boldsymbol{i} \leq \boldsymbol{j} \leq \boldsymbol{k} \right\}.$$

Result of K-mean Segmentation

fig A: input satellite image

fig B: input enhanced image

fig represent the result of K-mean segmentation indicating figure b are the outcome of image segmentation, In which figure (a) corresponds to vegetation, figure (b) corresponds to red soil, figure (c) corresponds to dry soil, figure (d) corresponds to housings, fig (e) corresponds to water bodies



fig(a)

fig(b)

fig(c)

fig(d)

fig(d)

B .Spectral-Spatial Features

In the original works on spectral-spatial image classification, image segmentation is used to distinguish spatial structures in a hyperspectral image. The pixel characteristic is the spectral reflectance of materials at the earth's surface, and the spatial context character is the spatial location in a two-dimensional coordinates. To improve the accuracy of classification and a suitable weighting factor is used to distinguish data points of different classes by combining the spectral feature with the spatial feature. Here we use the Curvelet Transform for spectral and feature extraction.

The curvelet transform is a multiscale directional transform that allows an almost optimal nonadaptive sparse representation of objects with edges. It has generated increasing interest in the community of applied mathematics and signal processing over the years

Curvelet Approximation

$$\boldsymbol{\|f - f_m^C\|_{L_2}^2 \sim 0((logm)3m^{-1/2})}$$

C. Dimension Reduction

Principal components analysis (PCA) is a widely used technique for dimensionality reduction (DR) and data compression. It uses Eigen values to determine the significance of principal components (PCs) so that DR is accomplished by selecting PCs in accordance with magnitude of their associated eigen values. An image pixel vector is calculated as:

$$X_i = [X1, X2, \ldots\ldots Xn]_i^T$$

with all pixel values *x1*, *x2*, ... *zN* at one corresponding pixel location of the hyperspectral image data. The dimension of that image vector is equal to the number of hyperspectral bands N. For a hyperspectral image with m rows and n columns there will be M=m*n such vectors, namely i=1,…,M. The mean vector of all image vectors is denoted and calculated as:

$$\mathbf{C_X = \frac{1}{M}\sum_{i=1}^{M}(X_i - m)(X_i - m)^T}$$

- The covariance matrix of **x** is defined as:

$$\mathbf{Cov(x) = E\{(x\text{-}E(x))(x\text{-}E(x))T}$$

where: **E** = expectation operator;
T superscript = transpose operation;
Cov = notation for covariance matrix.

- The PCA is based on the eigenvalue decomposition of the covariance matrix, which takes the form of:

Cx = ADAT

where **D** = diag(λ1, λ2...λN) is the diagonal matrix composed of the eigenvalues λ1, λ2...λN of the covariance matrix **CX,**

A is the orthonormal matrix composed of the corresponding *N* dimension eigenvectors **a***k (k=1,2,…, N)* of **CX** as follows: **A** = (**a**1, **a**2,…**a**N)

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1013 – 1018

- The linear transformation defined by:

$$\mathbf{y}i = \mathbf{A}T\mathbf{x}i \ (I = 1,2,\ldots, M)$$

is the PCA pixel vector, and all these pixel vectors form the PCA (transformed) bands of the original images.

D. Artificial Neural Network

Neural networks are a relatively new artificial intelligence technique. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The learning procedure tries is to find a set of connections w that gives a mapping that fits the training set well. Furthermore, neural networks can be viewed as highly nonlinear functions with the basic form:

$$F(X, W) = Y$$

where x is the input vector presented to the network, w are the weights of the network, and y is the corresponding output vector approximated or predicted by the network. The weight vector w is commonly ordered first by layer, then by neurons, and finally by the weights of each neuron plus its bias. The network that we have considered is a two layered ANN with 170 neurons. The number of input features for this network is 126 which further get optimised to 4 features. Figure 2 shows the ANN network. The network in this way is trained

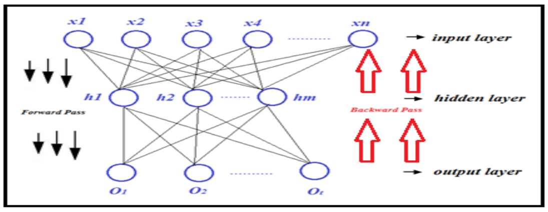

Figure 2: ANN Network

to classify the regions in hyperspectral image based on the type of geographical regions. We have obtained appreciable classification results. Figure 3 is the illustration of ANN training session. The training is carried out using the function trainlm and the performance evaluation is expressed in terms of Mean Square Error (mse).

3.Result and discussion

This system was proved to be efficient in classifying the hyperspectral images. Figure 4 are

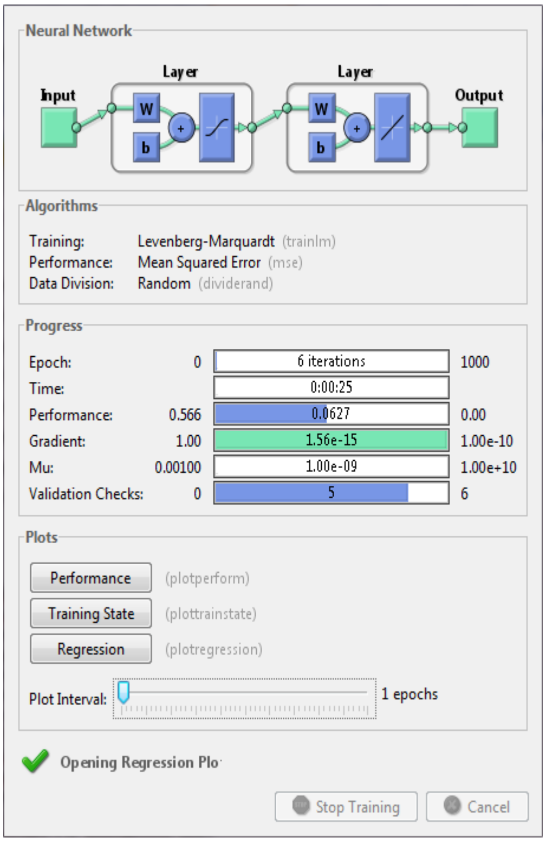

Figure3:ANN Training Session

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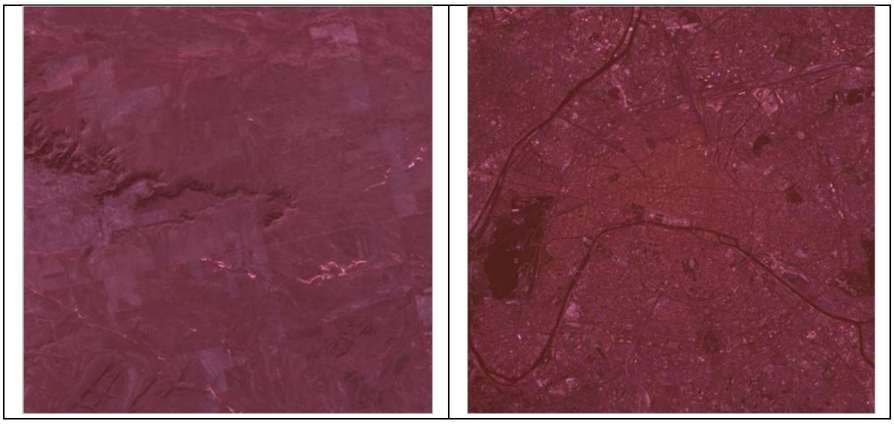

Figure 4: Hyperspectral Images (a) montana (b) paris

the hyperspectral images. Our work successfully classifies the mountain regions, forest areas, land regions and the water bodies in a given hyperspectral image.

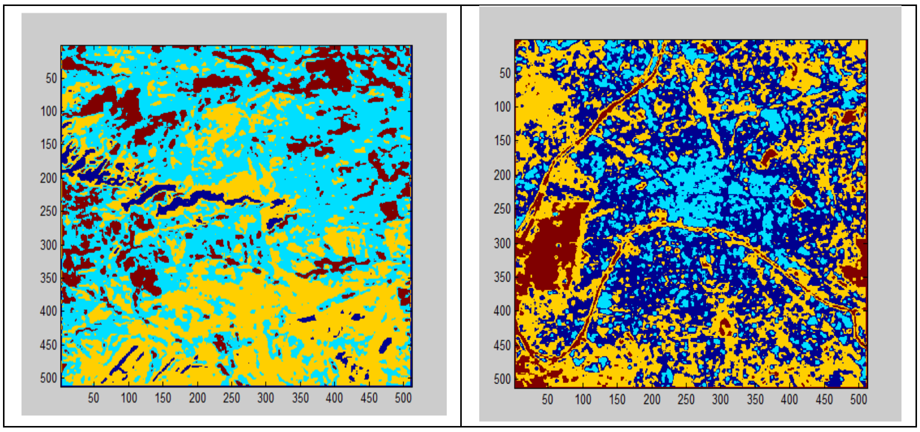

Figure 5: Result after classification

Figure 5 is the classified result of the original image. Figure 6 is the performance evaluation curve of the input image. Figure 7 is the regression plot of the input image obtained after classification. Table 1 shows the classification result of both the images.

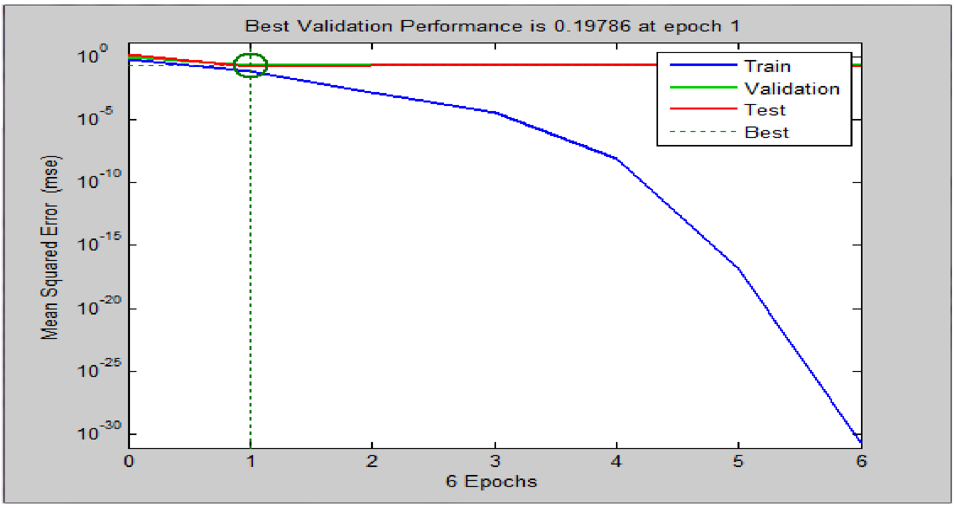

Figure 6: The Performance Evaluation Curve

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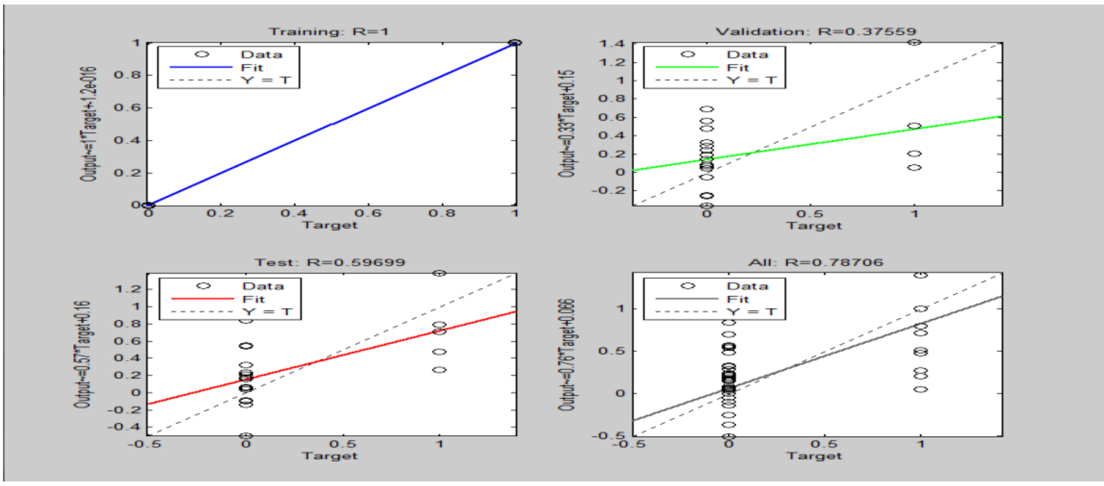

Figure 7: Regression Curve for ANN Training

Table 1: Classification of the geographical regions of both the images

Image \ Class	Mountain	Forest	Land	Water
montana	4%	47%	34%	14%
paris	43%	14%	33%	7%

Conclusion

We have presented a suitable method for classification of hyperspectral images with huge spatial homogeneous regions, when spectral reflectances of materials of different classes are of great differences. Although pixel characteristics of hyperspectral image are the only factor for effective classification, spatial characteristics have been used to compute the Laplacian Eigen values.

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