FEATURE EXTRACTION OF HYPERSPECTRAL IMAGES USING ELM CLASSIFIER

Jishma K. and Abdul Raouf M. T.
ECE Department, MEA Engineering College, Perinthalmanna, India
E-Mail: jishmanilambur@gmail.com

ABSTRACT

Hyperspectral images are the images that are taken using satellites. For the classification of these images, feature extraction is found to be an effective method. This paper mainly focuses on image fusion and recursive filtering. Firstly the image is divided into subsets of adjacent bands and then image fusion is adopted. For the better classification of features, recursive filtering is performed. The above methods along with the ELM classifier will increase the accuracy of classification. By using ELM, the overall accuracy and performance could be increased since ELM offers the advantages of smallest training error, good generalization ability, and ease of implementation as compared with other classifiers. Great superiority in computational speed especially for large-scale sample is also found in ELMs.

Keywords: ELM, hyperspectral images, image fusion, recursive filtering.

INTRODUCTION

Hyper spectral images are satellite images and are mainly affected by Hughes phenomena. As a result of Hughes phenomena, when the dimensionality of a data increases, the volume of the space increases so fast that the available data become sparse. The dimensionality of a data should be small for its better classification. There were lot of dimensionality reduction techniques proposed such as PCA [2], ICA [3], feature extraction [4], feature selection [5] etc. As far as feature selection is concerned, it selects a better subset from whole of the available subsets and preserves the physical meaning of the data. But it have some disadvantages also i.e. as the number of features increases, the dimensionality of data also increases and it will be difficult to select a better subset from the available subsets of data. Also, by using an assumption if we select a subset as the best subset, in reality it might not be the best. In case of PCA, the most of the information of images could be placed in its principal components, but it cannot consider the spectral features in it. In the case of ICA, the strong relationship between the neighbouring pixels was not considered. These all leads to a better dimensionality reduction technique called feature extraction.

In this paper a new classifier called ELM used for classification is proposed. The proposed feature extraction and classification method consists of four steps, i.e. band partitioning, image fusion, recursive filtering and classification.

PROPOSED APPROACH

The proposed method consists of mainly four steps. The image fusion is carried out before recursive filtering because it will become a tedious task to filter each and every band in the subsets and is also a time consuming process.

Band Partioning

The hyperspectral images are partitioned in to K subsets of bands depending on the frequencies of electromagnetic spectrum. Each subset consists of a large amount of bands.

Image Fusion

This technique aims in combining two images of a scene together and the fused image thus produced will be high in quality. Simple averaging method is used here which calculates the average image of each and every subsets and aims at the removal of noisy pixels and redundant information from these subsets. The block diagram of the proposed work is shown below.

Recursive Filtering

In order to obtain Kth feature, transform domain recursive filtering is performed on each fused bands. Recursive filter not only smoothens the image but also preserves its edge structures.

Classification

For the classification of IFRF features, ELM classifier is used.ELM is an efficient learning algorithm that is nowadays used for hyperspectral image classification. As compared to another classifier called SVM, ELM is very fast and it takes about zero seconds to get the training set where SVM takes about 15 seconds. The accuracy of ELM and SVM are same. The figures showing the smoothing of an image using ELM is depicted below. For this example, we take Indian Pines image as the input which is Figure-2 (a). Figure-2 (b)-(f) shows the smoothing images.

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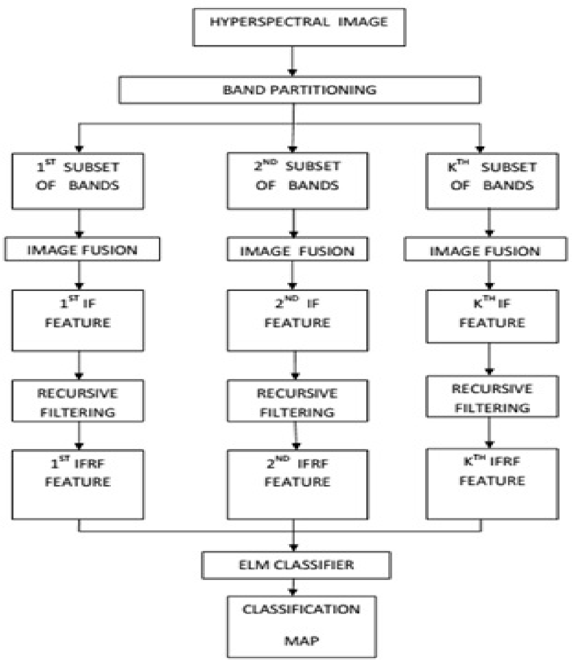

Figure-1. Block diagram of proposed work.

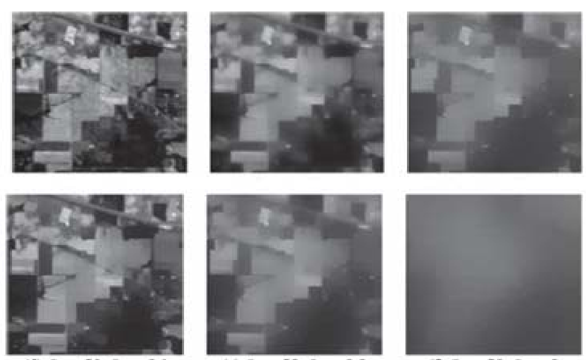

Figure-2. (a) Input Indian pines image, (b)-(f) Smoothing images.

EXPERIMENTS

Experimental Setup

- Dataset: Indian Pines Image is considered in this experiment. It reveals the agriculture details regarding the Indian Pine test site of North Western Indiana. AVIRIS sensor was used to capture it. This image consist of 145x145x220 size were only 200 bands are considered and the remaining 20 water absorption bands are removed. The Indian Pine image consists of 20m per pixel as its spatial resolution and its spectral coverage is from 0.4 to 2.5µm.

- Evaluation: In order to find out the performance of proposed method, Overall accuracy, Average accuracy and Kappa coefficients are used. Overall accuracy refers to the percentage of correct predictions made by the model with the actual classification in the test data. Average accuracy refers to the percentage of correct predictions made by the model when compared with the actual classification in test data. Kappa coefficient measures the relationship between beyond chance agreement nd expected disagreement.

Classification Results

Indian Pines Image which is considered as input in this paper consists of about 10249 elements in the dataset and only 10% of these elements are considered as the training set. As the number of features increases, it will affect the performance of classification. There are two important parameters for recursive filter i.e. spatial and range parameters. When these two parameters are of low and of high values, it will adversely affect the classification performance. So it is provided with default values and in this paper the value of spatial parameter is of 200 and the range parameter is of 0.3.

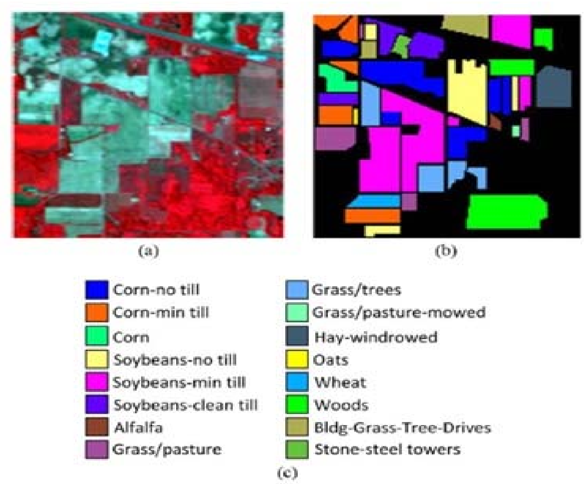

Figure-3 Indian pines data set. (a) Three-band color composite, (b) and (c) Reference data for Indian pines image.

In this paper, we consider 16 classes of Indian pines image. Figure-3 (a)-(c) shows the three-band color composite and the reference data for the Indian pines image. Figure-4 shows the ELM output of Indian pines image.

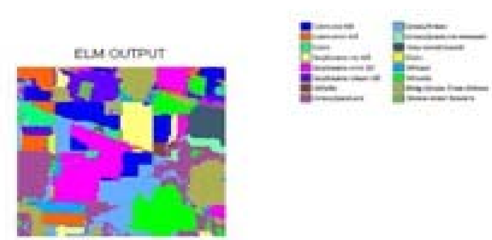

Figure-4. ELM output of Indian pines image.

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CONCLUSIONS

In this paper a new classifier for the feature extraction of hyper spectral images has been proposed. Experiments have been carried out in Indian Pines Image with its 10% as training set. The results of this experiment show that the proposed classifier is having better performance as compared with various pixel wise classifiers and spectral-spatial classifiers.

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