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An Adaptive Neuro Fuzzy Interference System for Feature Extraction of Hyperspectral Image

K. Hepsibah Persis
Assistant Professor – I
Dept of Electronics and Communication Engineering.
Velammal Engineering College.
Chennai, Tamil Nadu,India.
hepsi1986@gmail.com

Abstract

In this paper, a novel feature extraction method based on proposed for hyperspectral image classification. Hyperspectral images contain a large amount of data. Techniques are presented in this paper for visualizing important features contained in a hyperspectral data set. The major cause is that the size of training data set does not correspond to the increase of dimensionality of hyperspectral data. Actually, the problem of the "Finding minerals in hyper spectral images is too tough" emerges when a statistic-based classification method is applied to the hyperspectral data. It was discovered that the resulting image is heavily influenced by the choice of focus bands used for display. When averaging hyper spectral signatures, choosing the correct pixels makes a difference, and desirable results are not always obtained. It was discovered that a procedure for visualizing hyper spectral image data that uses the peaks of the spectral signatures of pixels of interest provides a promising method for visualization. Using wavelet coefficients and data from the hyperspectral bands produces noticeably different results, which suggests that wavelet analysis could provide a superior means for visualization in some instances when using bands does not provide acceptable results. The proposed Anfis (Adaptive neuro fuzzy interference system) method proves exceptional performance in terms of classification accuracy and computational efficiency.

Keywords: *Fuzzy interface network, Adaptive neuro network, Feature extraction, Hyper spectral image.*

INTRODUCTION

Hyperspectral technology has its unique advantages compared to another image processing. Hyperspectral images are images of high spectral dimensionality. Hyperspectral images contain a three dimensional radiation and spectral information. Hyperspectral image collects the same picture on many bands of the light spectrum (covering a waveband of O.4J.lm to 2.4J.lm), most in the visible and infrared areas, to generate a "data cube" that can reveal objects and information . The characteristics of spectral image in the traditional two-dimensional remote sensing based on an increase of spectral dimension, to form a unique three-dimensional remote sensing. thus has been widely used in many practical applications such as monitoring of the environment [1] and precision agriculture [2]. Hyperspectral technology geological mapping has low cost, low consumption, less than the cost of traditional geological mapping of one-tenth. For hyperspectral image classification, supervised classifiers such as Bayesian estimation method [3], decision tree [4], neural networks [5], [6], support vector machines (SVMs) [7], sparse representation [9], genetic algorithm [11], and kernel-based techniques. the dimension of the data space becomes higher, the number of training samples also exponentially, which indicates the Huge process. To solve these problems, many feature extraction methods have been proposed to reduce the spectral dimension of the hyperspectral data. In recent years, feature extraction and classification methods that full use of the spatial contextual information.

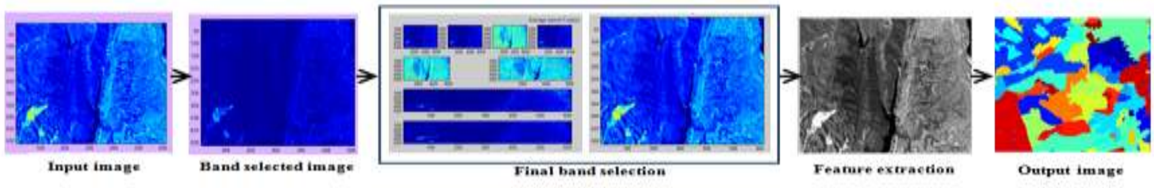
EXISTING SYSTEM

In this paper, a hyperspectral image feature extraction, the **SVM**, has been proposed. The proposed approach is based on the application of IF to reduce the dimension of the data, the use of recursive filtering to combine spatial information into the resulting **SVM** features. Experiments have been carried out on three different real hyperspectral images. The results of the experiments showed the effectiveness of the proposed method, which provided better results than those of the widely used pixel wise classifiers and the spectral–spatial classifiers. Moreover, the proposed method has presented several other advantages: 1) the feature can well preserve the physical meaning of the hyperspectral data. In other words, the pixel values in the feature image still reflect the spectral response of a pixel in a specific spectral range; 2) it is time efficient since it is based on a very fast EPF; and 3) although the classification accuracy obtained by the **SVM** is influenced by the number of features and the parameters of the recursive filter, these choices are not critical. The reason is that there is a large region around the optimal number of features for which the proposed method has similar results and outperforms other classification methods in terms of accuracy. Experiments are performed on different hyperspectral images, with the **support vector machines (SVMs)** serving as the classifier. By using the proposed method, the accuracy of the **SVM classifier** can be improved significantly. Furthermore, compared with other hyperspectral classification methods, the proposed adaptive neuro fuzzy interfence system method shows outstanding performance in terms of classification accuracy and computational efficiency. The disadvantage of the existing system shows low classification accuracies and high dimensionality.

PROPOSED APPROACH

Hyper-spectral images contain rich and fine spectral information, an improvement of land use/cover classification accuracy is expected from the use of such images. However, the classification methods that have been successfully applied to multispectral data in the past are not as effective as to hyperspectral data. The major cause is that the size of training data set does not correspond to the increase of dimensionality of hyperspectral data. Actually, the problem of the “Finding minerals in hyper spectral images is too tough” emerges when a statistic-based classification method is applied to the hyperspectral data. A simpler, but sometimes very effective way of dealing with hyperspectral data is to reduce the number of dimensionality. This can be done by feature extraction that a small number of salient features are extracted from the hyperspectral data when confronted with a limited set of training samples used to separate the minerals. In this paper, we tested some proposed feature extraction methods based on the wavelet transform to reduce the high dimensionality without losing much discriminating power in the new feature space.

BLOCK DIAGRAM



EXPLANATION

LOAD INPUT IMAGE

Hyper spectral image extracted from the satellite are taken as the input. The range of the hyper spectral. Image is 244 bands. Processing and storage of hyper spectral image are complex.

BAND SELECTION

The range of band with maximum image information is identified and selected. Thus the hyper spectral image dimension is reduced. Thus making storing and processing easy.

FINAL BAND SELECTION

By the process of image fusion selected range of band are fused in to single image to facilitate future the processing.

FEATURE EXTRACTION

The feature extraction is done by intrinsic image decomposition after converting the RGB image in to gray scale image .The reflectance components is taken in to account for future processing.

FIND ELEMENT

Based on the value of gray level co occurance matrix the color code of the image is obtained from the gray scale level.

ANFIS CLASSIFICATION

Adaptive Neuro Fuzzy Inference System is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about data set,in order to compute the membership function parameters that allows to track given input-output data. It serves as a basis for building the set of fuzzy if-then rules with appropriate member function to generate the input output pairs. In this design ANFIS is utilized as an estimator and controller.

PERFORMANCE MEASURES

The parameters like homogeneity, contrast, energy correlation are measured for both SVM classification method and ANFIS classification method. The measured quantity are compared with each another to show that ANFIS is better than SVM.

RESULTS

GENERAL

The system requirement for the project and its specification as follows:

HARDWARE REQUIREMENTS

Processor Type : Pentium -IV
Speed : 2.4 GHZ
Ram : 128 MB
RAM
Hard disk : 20 GB HD

SOFTWARE REQUIREMENTS

Operating System : Windows 7
Software Programming Package : Matlab R2010a

INPUT IMAGE

Hyper spectral image extracted from the satellite are taken as the input. The range of the hyperspectral. Image is 244 bands.

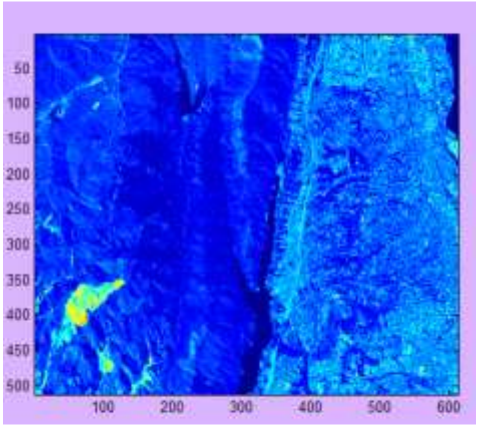


Fig 1. *Hyper Spectral Image*

OUTPUT IMAGE

The hyper spectral image reduced to 2D image

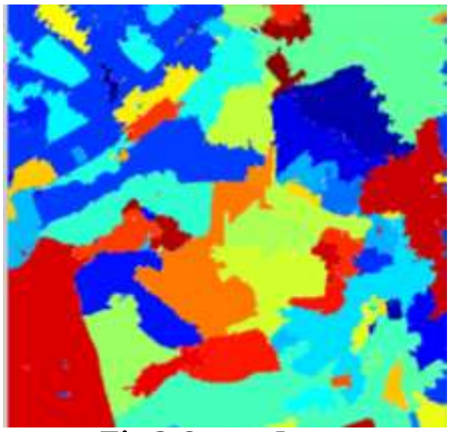


Fig 2.*Output Image*

Green Color - Tree
Red Color - Sand
Yellow Color - Sand Mountain
Orange Color - Pyramid
Blue Color - Home

GRAPH

The ANFIS classification is applied to obtain the following graphs.

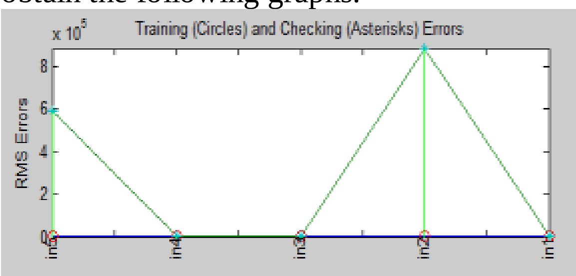


Fig 3. *Classification accuracy for homogeneity*

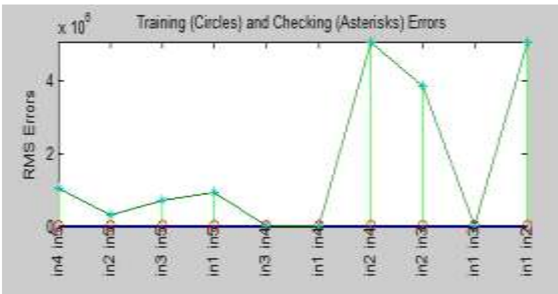


Fig 4. *Classification accuracy for contrast*

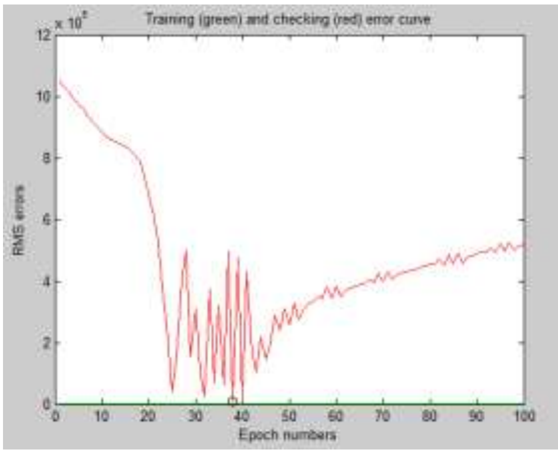


Fig 5. *Classification accuracy for energy correlation*

PERFORMANCE MEASURE

The parameters like homogeneity, contrast, energy correlation are measured for both SVM classification method and ANFIS classification method. The measured quantity are compared with each another to show that ANFIS is better than SVM**. Efficiency of ANFIS classification is found to be 98%.** ANFIS is shown to be better than the SVM method.

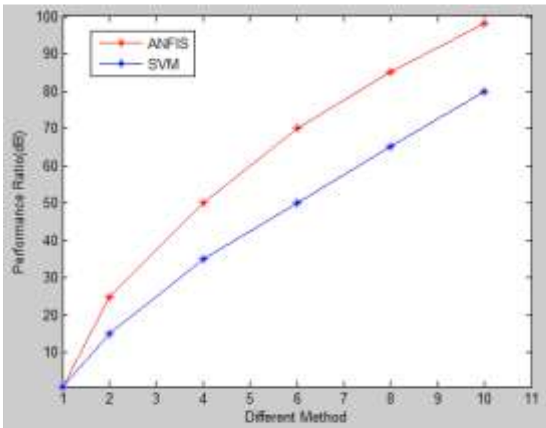


Fig 6. *Overall Classification Accuracy*

CONCLUSION

Hyperspectral image, like different spectral imaging, collects and processes data from across the spectrum. The goal of hyperspectral image is to get the spectrum for every pel within the image, with the aim of finding objects, distinguishing materials, or detection processes. Very much like the human eye sees visible radiation in 3 bands (red, green, and blue), spectral image divides the spectrum into more bands. This system of dividing pictures into bands is often extended on the far side the visible. Engineers build hyper spectral image sensors and process systems for applications in natural philosophy, agriculture, medicine imaging, geosciences, physics, and surveillance. Hyperspectral sensors look into objects employing a huge portion of the spectrum. Bound objects leave distinctive 'fingerprints' within the spectrum. Called spectral signatures, these 'fingerprints' alter identification of the materials that frame a scanned object. For instance, a spectral signature for oil helps geologists notice new oil field hyperspectral pictures contain made and fine spectral data, an improvement of land use/cover classification accuracy is anticipated from the employment of such pictures. However, the classification ways that are with success applied to multispectral knowledge within the past aren't as effective on hyperspectral knowledge. The key cause is that the dimensions of coaching knowledge set doesn't correspond to the rise of spatial property of hyperspectral knowledge. Actually, the matter of the “curse of dimensionality” emerges once a statistic-based classification technique is applied to the hyperspectral knowledge. A simpler, however typically terribly effective method of handling hyperspectral knowledge is to cut back the amount of spatial property. This can be done by feature extraction that a tiny low variety of salient options are extracted from the hyperspectral knowledge once confronted with a restricted set of coaching samples. during this paper, we have a tendency to tested some projected feature extraction strategies supported the wave remodel to cut back the high spatial property while not losing abundant discriminating power within the new feature house. Additionally, a brand new feature extraction methodology supported the matching pursuit with wave packet is employed to extract helpful options for classification. An knowledge set was tested for example the classification performance of the new methodology and be compared with the present wavelet-based strategies of feature extraction.

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