Satellite Image Classification using Neural Network

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ABSTRACT
The data from remote sensing have been used from so many years for image classification and its development algorithm, which can be applied to several different fields like forestry, educational purpose, management etc. In this paper, a classification method of a high resolution satellite image using neural network is proposed. First noisy bands were removed using dimensionality reduction technique. Minimum noise fraction (MNF) reduces the spatial dimension of hyperspectral image (HSI). Then, learning vector quantization (LVQ) based algorithm and some samples from groundtruth map are used to train the network for image classification and finally, accuracy is estimated. The main goal of this paper is to determine the ability of artificial neural network system for classifying satellite image by algorithm based on LVQ.

General Terms
Classification of hyperspectral image, neural network

Keywords
Hyper spectral image, minimum noise fraction (MNF), remote sensing, learning vector quantization, neural network, SVM (Support Vector Machine)

1. INTRODUCTION
Remote sensing is the method of obtaining the object or area by doing the analysis of images captured by a sensor or any device that is not near to the object or area under investigation. The most recent and significant invention in remote sensing is the advancement of hyperspectral sensors. Remote sensing has various applications like forestry, agriculture, biodiversity conservation, geology, education purpose, education purpose, regional planning, intelligence and warfare to identify exact locations.

Satellite image classification plays a significant role in remote sensing. In remote sensing, a process that attribute single pixels to a set of classes is called classification, while the segmentation is used for methods assembling pixels into object and then attributed to a class.

The excellent source of information for classification of materials is hyperspectral imaging. Hyperspectral image [1] consists of several numbers of spectral channels; the number may be in hundreds. Each channel occupies a small portion of electromagnetic spectrum. While comparing with multispectral image, it has a limited number of spectral channels which covers the large portion of electromagnetic spectrum. The classification process is specified as grouping all pixels into one of the distinct land cover classes in a digital satellite image. This grouped data is processed to create regional maps of the land cover class present in an image. There are generally 2 methods of classification of images i.e. unsupervised classification and supervised classification.

Despite the ample amount of research has been done for the classification in remote sensing, the classification of high-dimensional hyperspectral data using a few labeled samples is still an open research area [2].

It is very hard to study HSI specially due to high dimensionality of pixels, the specific noise and contingency sources observed. The strong collinearity issues are caused due to high spectral sampling of HSI (the bands which cover narrow portions of electromagnetic spectrum, typically 5-10 nm). Finally the spatial inconsistency of spectral signature increases the internal class variability. HSI image classification is a very difficult problem due to the few labeled samples. As a result, the accuracy acquired over multispectral image classification is generally adjusted when applied to HSI. Before the introduction of HSI, classifiers were parametric, such as maximum likelihood or linear discriminant analysis [3]. The multispectral images and the dimensionality of all these was usually remains between four and ten bands and it deal with the methods based on the covariance matrix. The dimensionality of pixels increases to hundreds in HSI. The standard parametric methods became unreliable because for the determination of covariance matrices, many labeled samples were required, which are usually not available.

A method for classification of satellite images having hyperspectral data is the main objective of this paper. The residual part of this paper is managed as follows. Section II gives idea about the methodology and the proposed scheme of classification. Experimental results and conclusion are described in section III and IV. Section V describes the future scope.

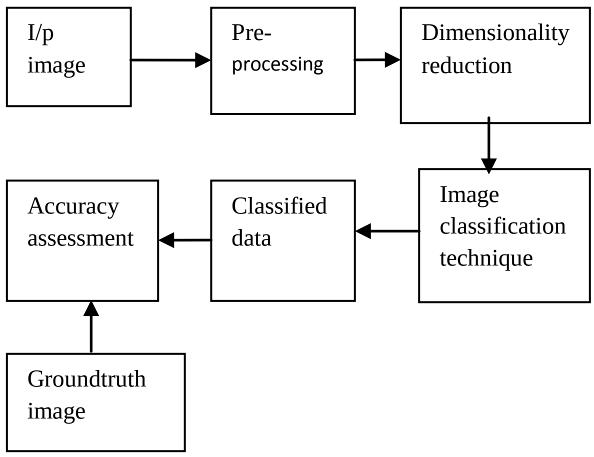
2. METHODOLOGY


Figure 1. Block Diagram

Methodology opted for the study has been shown in above Figure 1. The input satellite image is first preprocessed and then a dimensionality reduction approach is used to remove noisy bands and using MNF, we reduced 220 bands to 200. Then classification has done using neural network technique.

The dimensionality reduction approach and neural network technique is described below.

2.1 Dimensionality Reduction

We used DR technique because hyperspectral data live in lower sub-space than original spectral space. The contribution of dimensionality deduction is to remove the noisy bands i.e. one can perform in the space where hyperspectral data live, which significantly reduce the computational complexity, without sacrificing accuracy. In this paper, MNF [4]-[5] is used for dimensionality deduction because it is widely used and very effective for various hyperspectral imaging problem. MNF is based on standard deviation and signal to noise ratio.

First of all, we introduce the notations. Let X be an observed hyperspectral dataset and denoted by-

$$X = \{x_i \in R^N \ , i = 1, 2\ldots\ldots B\}$$

where, N is the number of pixels and B is the no. of spectral bands in X. We used MNF for dimensionality deduction with preservation of spectral information. After DR, X changes to Y, and it is denoted by-

$$Y = \{y_i \in R^N \ , i = 1, 2\ldots\ldots q\}$$

where, q is no. of spectral bands in Y and, q<<B.

2.2 Image Classification Using ANN

The processing node which corresponds to the neuron of human brain is the basic element of artificial neural network [6]-[8]. The processing node accepts a set of i/p values and sums it, this addition is then send through an activation function that provides the o/p value of node, which is processing node of next ANNs formed by one of the i/p of processing node of previous ANNs. The transfer function is used to minimize the no. of iterations. It improves the performance by introducing non-linearity into the network.

The ANNs has capability to learn which its most interesting characteristics are. The way by which the weights in the network are adjusted between consecutive training cycles or epoch is defined by the learning algorithm. The algorithm is operated by searching an error surface which is defined as weight function, using gradient descent technique [9] to locate the point which has less error.

The training depends on learning vector quantization. LVQ is a way for training a network in a supervised manner. The function lvqnet is key function in training algorithm. A problem arise in LVQ is the selection of a convenient measure of distance for training and classification. LVQ system is denoted by prototypes W = (w(i),.....,w(n)) which are defined in the feature space of observed data.

In LVQ algorithm, the prototype which is closest to the input according to a given distance measure can be determined. The position of so-called winner prototype is then adapted, and if the data point is properly classifies, then winner node is moved nearer whereas when it is misclassified or incorrectly classifies, the winner node is displaced away from i/p data point.

An input vector v is chosen at random from the large input space. If the class labels of the input vector 'g' and a voronoi vector 'h' equals, the voronoi vector h is moved in the direction of the input vector g. If the class labels of the input vector g and the voronoi vector h not same, then the voronoi vector h is moved away from the input vector g.

Suppose that the voronoi vector is the nearest to the input vector g_i. Let X_h denote the class associated with the voronoi vector and Lg_i denote the class label of the input vector g_i. The voronoi vector X_h is adjusted as follows.when,

$$X_h = \mathrm{L}g_i \qquad W_i(n+1) = W_i(n) + \eta\ [g_i - W_i(n)] \qquad (1)$$

$$X_h \neq \mathrm{L}g_i \qquad W_i(n+1) = W_i(n) + \eta\ [g_i - W_i(n)] \qquad (2)$$

where $0 < \eta < 1$.

3. EXPERIMENTAL RESULTS

The image used in proposed work was collected form aviris.jpl.nasa.gov/data/free-data.html. This scene was captured over the Indian Pines test site in North-western India by AVIRIS sensor and it consist of 145*145 pixels and 224 spectral bands. The range of wavelength is from 0.4 - 2.5 µm. The spatial resolution is 20 m per pixel. The Indian Pines scene contains 2/3rd of agriculture and 1/3rd of forest or other perennial vegetation.

The groundtruth is also available on the same link and it is designated into 16 classes. According to our requirement we have generated the groundtruth for 5 classes, 7 classes and 10 classes.The neural network toolbox in MATLAB R2010a is used for training purpose. The training set is trained using samples from ground truth data. Ground truth helps to identify the true type of classes as the sample training dataset is used to train the network. The following Figure 2 shows the training window.

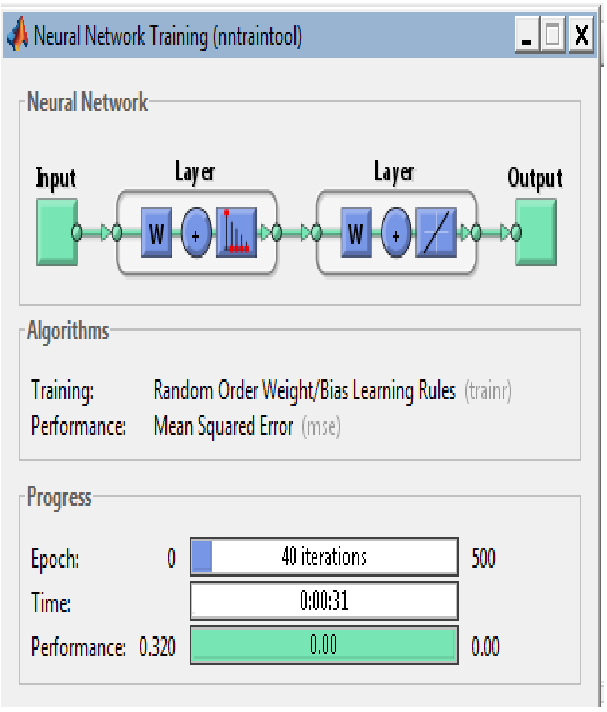


Figure 2. Training window

The syntax nntraintool indicates the toolbox of neural network training. The function of this tool is to opens neural network training GUI (graphical unit interface). The training was based on random order weights or bias learning rule.

Training has done using 10 samples of every class, taken from groundtruth map. The required performance for training of 5 classes met in 40 iterations.

We can access the additional plots, like confusion matrix, using nntraintool in neural network toolbox. The confusion matrix is the plot between target class and output class, indicating accuracy. The diagonal elements in matrix represents no. of perfectly classified pixels i.e. the no. of groundtruth pixels with a certain class name that actually obtained the same class name during classification. The strength of confusion matrix is that it identifies the classification error. The row represents the classes in groundtruth map while the column represents the classes in the obtained result. The diagonal elements indicate the no. of perfectly classified pixels and the off-diagonal elements represents misclassified pixels. The Figure 3 shows the training confusion matrix for classification of 5 classes and it is 100% accurate. All pixels were accurately classified in training then, testing has done and results are discussed below.

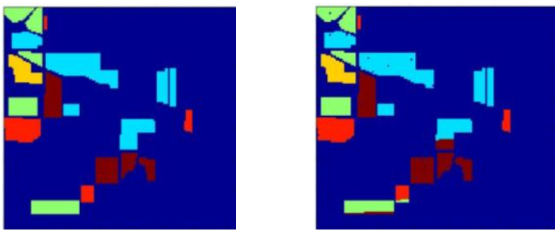
Target class

output class

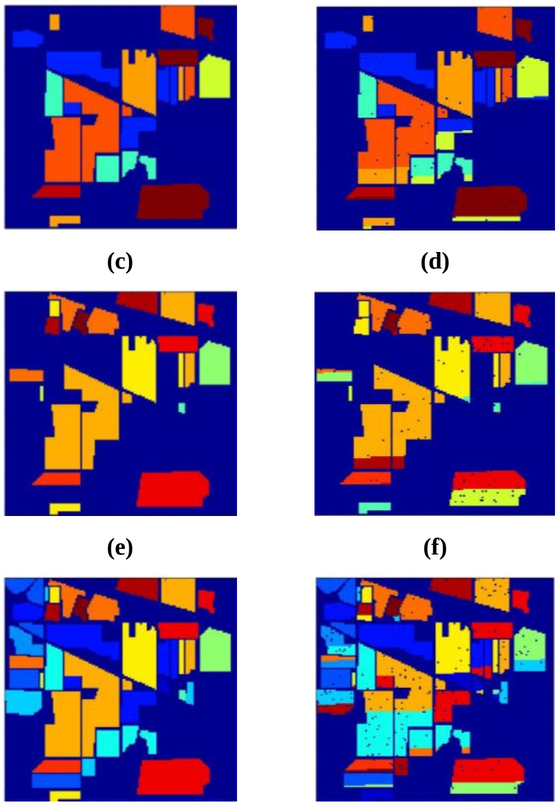
10 20.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
0 0.0%	10 20.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
0 0.0%	0 0.0%	10 20.0%	0 0.0%	0 0.0%	100% 0.0%
0 0.0%	0 0.0%	0 0.0%	10 20.0%	0 0.0%	100% 0.0%
0 0.0%	0 0.0%	0 0.0%	0 0.0%	10 20.0%	100% 0.0%
100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

Figure 3. Training confusion matrix

The following Figure 4 shows the results for classification of different no. of classes. The Figure 4 (a) shows the groundtruth map for 5 classes and 4 (b) shows the classified result for same 5 classes having accuracy 94.16%. Then, Figure 4 (c) shows the groundtruth map for 7 classes and Figure 4 (d) shows the classified map for that same 7 classes having 89.69% accuracy. Similarly Figure 4 (e) shows groundtruth for 10 classes and Figure 4 (f) shows the classified results for same 10 classes with 83.18% accuracy. And finally Figure 4 (g) shows the groundtruth map for all 16 classes and Figure 4 (h) shows output classified map with accuracy 72.67%.



(a) **(b)**



(c) **(d)** **(e)** **(f)** **(g)** **(h)**

Figure 4 (a) Groundtruth map containing 5 classes (b) classified output map containing 5 classes (c) Groundtruth map containing 7 classes (d) classified output map containing 7 classes (e) Groundtruth map containing 10 classes (f) classified output map containing 10 classes (g) Groundtruth map containing 16 classes (h) classified output map containing 16 classes.

To evaluate the performance of classified data, accuracy assessment is the most common technique. The higher the classification accuracy, the better system is performing. The classification accuracy is calculated as –

$$CA = \frac{no.of\ correct\ classified\ samples}{total\ no.of\ samples} \times 100$$

Where *CA* = Classification Accuracy

4. CONCLUSION AND FUTURE SCOPE

In this paper, we have presented a high resolution satellite image classification depends on neural network. The classification of hyperspectral image has been done correctly. The image has 16 classes namely Corn-no till, Corn-min till, Corn, Soyabeans-no till, Soyabeans-min till, Soyabeans-clean till, Alfalfa, Grass/pasture, Grass/trees, Grass/pasture-mowed, Hay-widrowed, Oats, Wheat, Woods, Stone steel towers, Buildings-Grass-Tree-Drives.

Table 1. Accuracy for different classes

Sr. no.	No. of Classes	Accuracy
1	5 Classes	96.95%
2	7 Classes	90.13%
3	10 Classes	84.26%
4	16 Classes	77.83%

In this paper, classification of satellite image has been done successfully for different classes and the above Table 1 describes the accuracy of classification for different no. of classes for the same hyperspectral image.

In future, the work may be done to classify the Very high resolution (VHR) satellite images using neural network. As LVQ is adopted for classification in the proposed method, in future, we will consider another algorithm like Self organizing map (SOM) or any other competitive learning method for classification of VHR satellite images.

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