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# Remotely Sensed LANDSAT Image Classification Using Neural Network Approaches

**Smriti Sehgal**
Department of Computer Science & Engineering, Amity University, Noida, India

## ABSTRACT

**In paper, LANDSAT multispectral image is classified using several unsupervised and supervised techniques. Pixel-by-pixel classification approaches proved to be infeasible as well as time consuming in case of multispectral images. To overcome this, instead of classifying each pixel, feature based classification approach is used. Three supervised techniques namely, k-NN, BPNN and PCNN are investigated for classification using textural, spatial and spectral images. Experiments shows supervised approaches perform better than unsupervised ones. Comparison between k-NN, BPNN, and PCNN is done using these features and classification accuracies for BPNN is found out to be more than k-NN and PCNN.**

**Keywords** - **Classification, multispectral image, neural network, spatial feature, Textural feature.**

## I. INTRODUCTION

Remotely sensed satellite image having multispectral bands gives large amount of data about the ground interested in. The size of images is growing due to advancement in sensors capturing them. Processing of such images poses challenges such as choosing appropriate bands, extracting only relevant features, classification etc due to spectral and spatial homogeneity. Using only spectral information from multispectral image is not sufficed for classification purpose. Combining either textural or spatial information with spectral information increases the classification accuracy of the system.

Various spatial features are extracted from the image such as length, width, PSI, ratio etc using the concept of direction lines [5]. Gray level co-occurrence matrix (GLCM) [7] is mostly used and successful to some extent, and it is used to find textural features from the LANDSAT image. In [6], a new feature similarity measure is introduced, known as maximum information compression index, MICI [6]. This approach is based on linear dependency among the variables and benefit of choosing this measure is that if we remove one of the linearly dependent feature, data would still be linearly separable. After extracting and selecting appropriate features from the image, these features are given as input into classifiers for further processing. Several classification approaches such as k-means [8], SVM [4], BPNN [2][8], and PCNN are used. In [9], neural network techniques are presented and compared for remotely sensed multispectral image.

In this paper, LANDSAT ETM+ multispectral image of Brazil is used for experiments and result analysis. First, loading of multispectral image is achieved using PCA technique, which reduced the number of bands of this image from seven to three. Second, textural and spatial features are extracted using GLCM and PSI. Structural feature set [4] is constructed using these features. Third, relevant features are selected using S-Index [6] approach. Fourth, both the feature set along with spectral features is given as input to different classifiers. Classification accuracy is calculated and then compared among each classifier.

This paper is organized as follows: section II gives the detailed specifications of image and its reference data. Section III describes the different features extracted, feature selection approach, and classification techniques. Section IV gives the design flow. Section V shows the experimental results and section VI concludes the paper.

## II. DATA ACQUISITION

LANDSAT ETM+ image used, consist of 7 spectral bands with a spatial resolution of 30 meters for all bands. The used LANDSAT has good quality of sensor distortion, acquired on 20 January, 2000. The image has 0.1 micrometer spectral resolution and 30 m spatial resolution. Dimension of image is 169 × 169 with TIFF extension. Ground truth data was available with the image as a reference for processing on the image.


**Figure 1: Ground Truth Data**

Using available ground data, seven classes are known in the image. The search program begins by examining blocks of pixels looking for spectrally homogeneous blocks. Data samples created from this counted to total of 122 samples. Out of these, approx

74 were used as training samples and rest are kept as testing samples.

## III. METHODOLOGY

### 3.1 Textural Features

GLCM [7] is used to extract textural features from the image. A statistical method that considers the spatial relationship of pixels is GLCM, also known as the gray-level spatial dependence matrix. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but other spatial relationships between the two pixels can also be made. Each element (I, J) in the resultant GLCM is simply the sum of the number of times that the pixel with value I occurred in the specified spatial relationship to a pixel with value J in the input image. The Following GLCM features were extracted: Contrast, Dissimilarity, entropy, Homogeneity, GLCM Mean, GLCM variance, GLCM Standard Deviation.

### 3.2 Spatial Features

Shape and structural features are extracted using PSI [5] and SFS [4]. Pixel Shape Index method uses the concept of direction lines for shape feature. In [5], direction lines of each pixel are determined using following rules: 1) Pixel Homogeneity of $i^{th}$ pixel is less than a predefined threshold T1. 2) The total number of pixels in this direction line is less than another predefined threshold T2. Theoretically, T1 will be set to between 2.5 to 4.0 times the averages SD of the Euclidean distance of the training pixel data from the class means [4]. T2 is set as 0.5 to 0.6 times the number of rows or columns for the image [4]. Length each direction line is find and PSI is calculated as in [5].

Statistical measures will be employed to reduce the dimensionality and extract the features from the direction lines histogram. Following statistical measures are extracted: Length, Width, Ratio, and SD from the histogram.

All spatial features together form Structure Feature Set, SFS.

### 3.3 Feature Selection

Feature selection is the process of removing features from the data set that are irrelevant with respect to the task that is to be performed.

The task of feature selection involves two steps, namely, partitioning the original feature set into a number of homogeneous subsets (clusters) and selecting a representative feature from each such cluster. Partitioning of the features is done based on the k-NN principle using MICI [6]. In doing so, the k nearest features of each feature is computed first. Among them the feature having the most compact subset is selected, and its k neighboring features are discarded. The process is repeated for the remaining features until all of them are either selected or discarded.

After all features are clustered into some clusters, one representative feature from each cluster is selected. For this, Mean of all the features in one cluster would represent a cluster.

### 3.4 Classification

Classification processing step classifies each block or pixel into one of the known classes. Backward Propagation is probably the most common method for training forward-feed neural networks. A forward pass using an input pattern propagates through the network and produces an actual output. The backward pass uses the desired outputs corresponding to the input pattern and updates the weights according to the error signal. A PCNN is a two-dimensional neural network. Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel's color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them.

## IV. DESIGN FLOW

Following Fig. 2 shows the steps to process multispectral LANDSAT image.

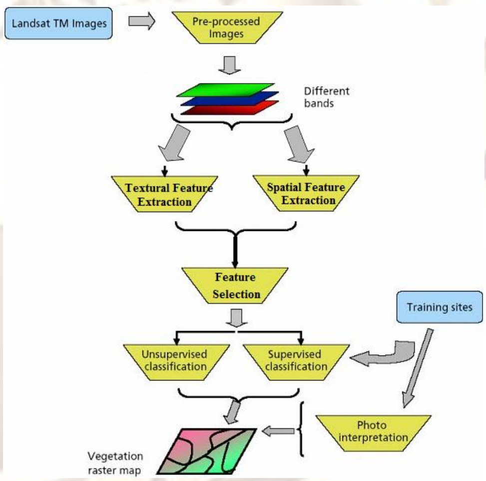


**Figure 2: Classification flow of MSI**

Noise removal and dimension reduction are performed in preprocessing step. K-means, an unsupervised technique i.e. no need of prior knowledge about image, is applied. Textural, spatial and spectral features are found out and then feature selection is performed. Several classification approaches, unsupervised and supervised, are performed. K-nearest neighbor, BPNN and PCNN, supervised techniques, are also applied. Training data is fed into supervised classifier as an external input to support classification step. Classification accuracy is calculated and compared for all the classifiers.

## V. EXPERIMENTAL RESULTS

LANDSAT image of Brazil is used for experiments. Original number of bands in image was seven, which was reduced to three using PCA. Image after selection of bands is as below:

**Figure 3: Selected band image**

k-means method was then applied to above image to perform pixel-by-pixel classification. Resultant classified image is as follows:

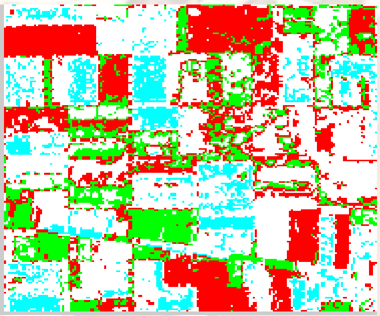

**Figure 4: K-means classified image**

In above image, each color corresponds to distinct class mentioned in Fig. 1. Classification accuracy for k-means approach found out to be 67.75%.

Textural features such as mean, variance, contrast, dissimilarity, entropy, homogeneity, and SD are extracted from band selected image using GLCM. Spatial features mentioned in section 3, are also extracted from band selected image. Selected features along with training data are fed into all supervised classifiers. Training data and pixel distribution formed using available ground data is given in Fig. 5 and table 1.

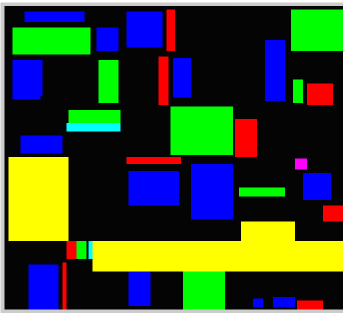

**Figure 5: Training Data**

**Table 1: Pixel distribution of image**

| Class No. | Total Pixels | Training Pixels | Testing Pixels |
|---|---|---|---|
| 0 | 4373 | 2624 | 1749 |
| 1 | 8375 | 5025 | 3350 |
| 2 | 7679 | 4608 | 3071 |
| 3 | 251 | 151 | 100 |
| 4 | 1756 | 1054 | 702 |
| 5 | 42 | 26 | 16 |
| 8 | 6085 | 3651 | 2636 |

In k-NN, k-nearest neighbor, k represents the number of clusters to be performed. Metric used for cluster formation is Euclidean distance. Table 2 and table 3 gives classification accuracies for different values of k for textural with spectral features and spatial with spectral features.

**Table 2: Classification Accuracies for different k values in k-NN using textural with spectral features**

| k | Classification Accuracy |
|---|---|
| 1 | 66.923% |
| 3 | 71.794% |
| 5 | 74.358% |

**Table 3: Classification Accuracies for different k values in k-NN using spatial with spectral features**

| k | Classification Accuracy |
|---|---|
| 1 | 76.67% |
| 3 | 74.35% |
| 5 | 78.12% |

Neural network model used in these experiments consist of three layers, one input layer, one hidden layer and one output layer. Numbers of neurons in input, hidden and output layer are seven, five, and seven respectively for textural with spectral features. Numbers of neurons in input, hidden and output layer for spatial with spectral features are four, three, and seven respectively. Initially, weights of the neurons are taken randomly. Error tolerance is taken as 0.001 and maximum number of epochs is set to 1000. After setting all parameters of the model, features are given as input to both the classifiers. Classified image by BPNN and PCNN is shown in Fig. 6 and Fig. 7. Classification accuracies found out to be as follows:

**Table 4: Classification accuracies for all methods with both feature set**

| Feature Set | Method | Accuracy |
|---|---|---|
| Textural + Spectral | k-means | 67.75% |
| | k-NN | 69.14% |
| | BPNN | 79.47% |
| | PCNN | 70.09% |
| Spatial + Spectral | k-means | 67.75% |
| | k-NN | 72.45% |
| | BPNN | 87.12% |
| | PCNN | 82.34% |

## VI. CONCLUSION

Previous work showed that feature based classification overcomes the drawbacks of pixel based classification approach. Detailed study of the image shows that wide information is spread over all spectral bands. Experiments are conducted first taking textural and spectral features together and then spatial and spectral features. Giving these feature sets as input to different classifiers, we compared the results. According to the table 4, feature based supervised classification gave better results than unsupervised one. Among the supervised techniques, BPNN gives highest accuracies for both textural and spatial features along with spectral features.

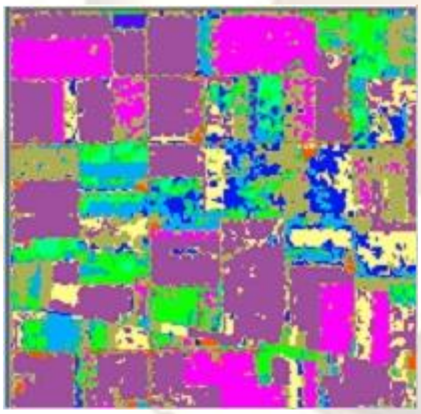

**Figure 6: Classified image by BPNN giving 87.2 %**

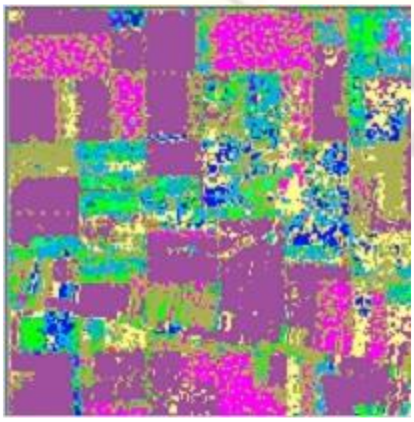

**Figure 7: Classified image by PCNN giving 82.34 %**

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