

Classification of Satellite Images Using Perceptron Neural Network

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Abstract

Image classification is an important part of digital image analysis and is defined as a process of categorizing the pixels into one of the object classes present in the image. As a prerequisite to image classification, a number of processes such as image enhancement, segmentation and feature extraction are required. This paper presents the classification of satellite images using Perceptron Neural Network with the transfer function hardlim and the learning rule learnpn. Before classification, the enhanced images are divided into a number of blocks and feature extraction is carried out using Principal Components Analysis (PCA). As color plays an important role in differentiating the objects in the satellite images, color information is used in extracting significant features. Fifty images from Landsat are used for training and testing of the results. The objects in the categories of water, land and vegetation are identified based on RGB components. Accuracy assessment and comparison is carried out using confusion matrix. It is concluded that choosing an appropriate block size affects the classification accuracy.

Keywords: Image Classification, Principal Components Analysis, Perceptron, Multispectral Images, Landsat Imagery

1. INTRODUCTION

Image classification has always been an important issue in any image processing system. The information obtained from classification process of remote sensing images is widely used in a number of applications like urban planning, agriculture, natural resource management etc. The objective of image classification is to categorize the pixels in the digital image into one of the object classes present in the image (e.g. land,

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vegetation, water, clouds etc.). The information thus obtained may be used for producing thematic maps for a number of applications.

The process of classification is mainly dependent on the type of learning approach that can be either supervised or unsupervised. In supervised approach, the labels for the target data needs to be specified as data to the classifier whereas in unsupervised approach, the targets need not be supplied. A number of classification techniques are available for identifying object classes in digital images. The statistical methods such as maximum likelihood classification may not produce highly accurate results. On the other hand, the techniques based on machine learning such as Artificial Neural Network (ANN) and Support Vector Machine (SVM) produce high accuracy even from fewer training examples as compared to their statistical counterparts.

Neural Networks is one of the popular techniques in computational intelligence in the area of machine learning and artificial intelligence. It is based on working of biological neurons in the human body that are capable of complex computations. A neural network comprises of a number of layers, one each for input and output and one or multiple hidden layers. The input layer nodes correspond to data sources, the output layer nodes refer to number of object classes to be recognized and hidden layer nodes carry out the task of computation. Perceptron, Multilayer Perceptron (MLP), Radial Basis Function (RBF) are few types of neural networks. Neural networks are non-parametric in nature and they do not assume any prior knowledge about data distribution. In the supervised approach used for training a neural network, the network must be taught the characteristics of dataset being used in the study. The neural networks are designed in such a way that they learn to adapt the weights of nodes in input and hidden layers. With each iteration, the weights are used by learning functions in order to compute the error rate. Based on error rates, the Neural Network progresses towards producing better classification results.

The selection of suitable techniques for image classification may differ from one application to another. Choosing a suitable classification technique for better interpretation of object classes in remotely sensed images is a difficult task. In case of remotely sensed images, images are captured without physical contact with ground surface. A number of different sensors are used to capture the images over various regions. Such images include satellite and aerial images and these images prove useful in the fields such as determining land use patterns, environmental analysis, weather forecasting, vegetation monitoring and other related areas. Image enhancement is often required for satellite images in order to identify the objects and extract features and their coordinates from images.

For satellite images, a number of databases are available such as Landsat, Google Earth, Imageseer and so on. For the research work presented in this paper, a number of Landsat images are downloaded with the help of Earth Explorer (<https://earthexplorer.usgs.gov>). Landsat is a remote-sensing satellite program operated by National Aeronautics and Space Administration (NASA). It is an ongoing series of satellites that conduct Earth observations. The purpose of Landsat is to archive images of earth and gather facts about natural resources of our planet. Though individual small

elements may not be visible in these images but large structures are clearly visible for analysis and interpretation.

As the advancements in new technology is gaining pace, the multispectral satellite images can be easily represented in digital format which can be analyzed for a range of applications with the help of computer systems. Landsat data has been used to support wide range of applications and is used by government, commercial, industrial and educational communities throughout the world. The classification of satellite images is useful for research, agriculture, change detection, forestry, mining and many more to mention.

Satellite images consist of multiple bands and are called multispectral images. The objects present in these images have unique spectral signatures that are useful in identification of different classes present in an image. For this research, the visible RGB bands have been used. It has been observed that even with RGB bands it is possible to obtain a lot of information that can be very useful in analyzing the object categories. The color features in the images have been used as the basis for feature extraction and classification. A color is usually assigned for every object class that needs to be identified in the image.

This paper presents a technique for classification of satellite images using Perceptron Neural Network and is organized in five sections. Section 1 provides brief introduction about Image Classification, information in satellite images and various classification techniques with respect to satellite images and Section 2 summarizes the literature review on classification methods. Section 3 describes Methodology used including Design, Feature Extraction using multi-block PCA and Image Classification using Perceptron Neural Network. Results are presented in Section 4. Section 5 includes the conclusions and scope for future work followed by Section 6 with references.

2. LITERATURE REVIEW

Qiu et al. illustrated the use of multi-block PCA for change detection in remotely sensed images. The authors proved the use of multi-block PCA in image interpretation and better description of results. The images are divided into a number of blocks of size 40X40 pixels that are further used to extract principal components. The computational cost of traditional PCA and MB-PCA were almost same. Only one band dataset was used for the study conducted for the paper which can further be extended to multiple bands [1].

Cetin et al. stated thematic maps as invaluable source of information for a number of investigations as they provide spatial as well as temporal information about objects and materials on earth surface. The classification algorithms employed for producing thematic maps prove beneficial in complex classification problems. The images used in the study were taken from Landsat ETM+ and Terra ASTER. The input to the neural network are the image band combinations. They proved that the neural network are used in a number of applications involving extracting land cover information through multispectral satellite images [2]. Kavzoglu et al. explained the use of artificial neural

networks (ANNs) w.r.t satellite images and proved that ANNs produce higher classification accuracies by employing fewer training samples [3].

Eeti et al. presented Multi-Classifer System (MCS) to analyze high spectral satellite image from worldview-2 sensor. The authors used MCS in landuse-landcover (LULC) classification avoiding any loss of information. They also presented a comparative study of classification results obtained through the use of principal components by single classifier and by using all spectral channels in MCS. The results demonstrated that utilizing all channels in MCS in five ANN classifiers improves accuracy as compared to a single ANN that used first three principal components for classification process. [4]

Najab et al. presented a holistic feature extraction based on principal component analysis for the classification of small living areas in high resolution satellite images. The authors used a moving window for larger images to resample the testing images. They used 80X80 and 40X40 pixel windows for resampling the training images. The training sets were formed by cropping the portions showing the presence of settlements of size 80X80 and 40X40 from large satellite images. They used 50 images for each set as training set. Results were compared using a reference map. They concluded that accuracy of classification is dependent on purity of training images instead of number of images and also on size of sliding window that is used for training and testing [5]. The usefulness of PCA for feature extraction is explored for processing of multispectral remote sensing images [6]. Sergi et al. presented the application of principal components analysis in the classification of Landsat multispectral images. The authors used a small learning database and compared three neural network architectures Perceptron (MLP), Self-Organizing Feature Map (SOFM) and Hybrid Learning Vector Quantization (HLVQ) using principal components as inputs. The results are compared based on recognition rates and reconstructed images [7].

Mahmon et al. used ANNs for classification of satellite images. They used back-propagation and kmeans for classification. Performance of Image Classification was compared through overall classification accuracy and Kappa coefficient [8]. Silva et al. analyzed the results and inferred that Artificial Neural Networks are good pattern classifiers for multispectral images and generate similar results as PCA+ANN [9].

Li et al. presented a comparison of pixel-based and object-oriented methods for classification of high-resolution satellite imagery. They used object-oriented image analysis and presented a supervised procedure in order to reduce manual labour and to identify object features and threshold values for classification. Detailed discussion was presented on image segmentation, feature selection, object classification and error balancing. An image from Quickbird, a standard dataset for multispectral images is taken for analysis of the two methods and they concluded that object-oriented classification is more efficient in extraction of information from high-resolution satellite imagery as compared to pixel-based method [10].

Peacock assessed and compared the accuracy of supervised and unsupervised classification by use of Landsat Imagery of three study areas in Little Rock, Arkansas. The study images were obtained from Landsat 7 Enhanced Thematic Mapper Plus

(ETM+). The author used error matrices and Kappa coefficients for comparison of results of classification approaches for land cover compositions containing homogeneous, intermediate, and heterogeneous areas [11].

Wang et al. explained the use of Pixel-based classification and object-oriented classification. Blocks of images are used as training samples. The authors performed multi-class classification on the image blocks for comparing two approaches. A subset of the ground truth images were used for training the classifiers and then applied to the remaining images. The classification rate is given as the percentage of the images that were labelled correctly [12].

3. METHODOLOGY

3.1 Dataset

The dataset is created by downloading 50 images from Landsat Image Gallery from the website <https://earthexplorer.usgs.gov/>. In these images, different object categories like water, vegetation and land may be present as shown in Figure 1. Some of the sample images of earth taken from Landsat satellite containing these classes are shown in Figure 2.



Figure 1. Image showing object categories: land, vegetation and water.



Figure 2. Sample Images of Earth

As a part of pre-processing step, each image was first enhanced using contrast stretching [13]. Different sets of enhanced images were used for generating training and test datasets. The training and test datasets are created by extracting parts of these images from the areas indicating the presence of Water, Land and Vegetation which are also termed as Regions of Interest (ROIs) corresponding to classes. For better interpretation of object classes, a classification color is assigned to each object class that needs to be recognized by a classification algorithm. Usually, vegetation is represented by green color, water by blue color, soil using brown or grey color, snow by white color and so on. The sizes of these blocks from images are taken as 16X16 and 8X8 pixel based on size of objects in the satellite images. Total 150 blocks (50 in every class) each for training and test dataset for both block sizes are collected.

3.2 Feature Extraction

Since the satellite images contain huge amount of information in multiple bands, there arises the need of feature extraction that reduces the input in the form of features that acts as input to a classification algorithm. The features generated may be large in number but only required number may be used for classification.

Principal Component Analysis (PCA) has been widely used as a technique for dimensionality reduction for data analysis. It finds its importance as the most popular technique for reducing data dimensions in case of remotely sensed images. For this paper, feature extraction is performed using Principal Component Analysis (PCA) on a set of blocks/subimages obtained from training and testing image. This version of PCA has been referred as Multiblock PCA [1] but a variation has been implemented on the R, G and B color bands separately for the three classes of land, vegetation and water. Also, different block sizes (16X16 and 8X8 pixels) are chosen for experiments. Focus is given on color feature as it can easily be used for discriminating various object categories in satellite images.

For 16X16 pixel block size, for three RGB components, 50 training images for each object class are converted into column vectors to create matrices of size 256X50. This matrix is used to compute 64 principal components corresponding to each RGB component image for land, vegetation and water categories resulting in a combined feature matrix of size 192X150 for training dataset. The same process of feature extraction is repeated for 50 test images for each object class resulting in combined feature matrix of size 192X150 for test dataset. Similarly, for 8X8 pixel block size, for three RGB components, 50 training images for each object class are converted into column vectors to create matrices of size 64X50 which is used for obtaining 16 principal components corresponding to RGB component images for land, vegetation and water categories resulting in a combined feature matrix of size 48X150 for training dataset. The same process of feature extraction is repeated for 50 test images for each object class resulting in combined feature matrix of size 48X150 for test dataset. 1/4th of the total number of features obtained from covariance matrices are used for classifying objects.

3.3 Image Classification Using Perceptron Neural Network

The principal components for three classes are used as inputs for training the Neural Networks. Perceptron Neural Networks (PNN) is used for classification with hardlim as transfer function and learnpn as learning rule. The hard limit (hardlim) transfer function generates either 0 or 1 as output and learnpn is a weight and bias learning function. When input vectors have different magnitudes, it can result in faster learning rate.

Training image features and targets are input for training the perceptron whereas test images features are used for simulating the network for predicting the classes. One-vs-all approach has been followed for classification of more than two object classes. A group of more than one classifier are used for building a multi-class classifier model using perceptron. Here, three classifiers are created with two classes each in both 16X16 and 8X8 pixel block sizes. The first classifier, Classifier1 is created by taking land as one class and combined vegetation and water as other class (not land). Similarly, Classifier2 is designed with vegetation as one class and combined land and water as other class (not vegetation) and Classifier3 considering water as one class and combined vegetation and land as other class (not water).

Target patterns are defined for each classifier based on block images of water, land and vegetation classes as a part of supervised learning for Neural Network. Also, one-to-one strategy is followed for defining target patterns. For both 16X16 and 8X8 pixel block sizes, three classifiers each for land, vegetation and water are trained with training images and simulated using test images.

4. RESULTS

The classification results for 16X16 and 8X8 pixel block sizes obtained using Perceptron Neural networks with hardlim as transfer function and learnpn as learning rule are given in Table 1. In both cases, accuracy with a set of 150 known images was 100%. Using 150 test/unknown images, the variation in results for three classifiers for land, vegetation and water are also shown. The classification accuracy is calculated as average of results obtained from three binary classifiers.

Table 1. Classification results obtained using Perceptron (1000 epochs).

S.No	Block Size	Feature Dimensions	Classification Accuracy with Training Images	Classifier1 (for land)	Classifier2 (for vegetation)	Classifier3 (for water)	Overall Classification Accuracy with Test Images
1	16X16	192	100%	66.7%	98.0%	97.3%	87.3%
2	8X8	48	100%	98.0%	94.0%	98.7%	96.9%

Table 2. Confusion matrices (Column 1) from 3 binary classifiers for 8X8 pixels block-images for test images for land, vegetation and water classes.

Classifier				Accuracy	Misclassification Rate	
(a)	No. of Samples = 150		Predicted		0.98	0.02
			Land	Not Land		
	Actual	Land(50)	TP=47	FN=3		
		Not Land(100)	FP=0	TN=100		
(b)	No. of Samples = 150		Predicted		0.94	0.06
			Vegetation	Not Vegetation		
	Actual	Vegetation(50)	TP=41	FN=9		
		Not Vegetation(100)	FP=0	TN=100		
(c)	No. of Samples = 150		Predicted		0.987	0.0133
			Water	Not Water		
	Actual	Water(50)	TP=48	FN=2		
		Not Water (100)	FP=0	TN=100		

Confusion matrices are generated for evaluating the classification results. First column in Table 2 shows confusion matrices from three binary classifiers for 8X8 pixel block-images from test images for land, vegetation and water classes showing the correct and incorrect prediction for every class. TP, FP, FN and TN denote True Positive, False Positive, False Negative and True Negative respectively. Second and third columns in Table 2 depict the accuracy and misclassification rates. For example, the first confusion matrix (a) for binary classification of land as one class and (vegetation+water) i.e, not land as second class shows that out of 50 instances of land class, 47 have been correctly identified and 3 have not been identified as land. The accuracy and misclassification rates are calculated as

$$\text{Accuracy} = (\text{TP} + \text{TN}) / \text{No. of Samples}$$

$$\text{Misclassification Rate} = (\text{FP} + \text{FN}) / \text{No. of Samples}$$

The Neural Network toolbox in MATLAB is used for the experiments. The classification accuracy is computed using confusion matrices obtained based on combined RGB features of the three classes and then finding average as overall accuracy.

5. CONCLUSION AND FUTURE WORK

Based on the experimental results obtained by using supervised training of Perceptron Neural Networks, it can be observed that perceptron produces satisfying results for linear features. Also, one-vs-all approach can be used for multiclass classifier by combining multiple binary classifiers. The evaluation of classification accuracy is

based on confusion matrices. The comparison is done by performing classification based on combined RGB features for three object classes of land, vegetation and water. It is concluded that choosing an appropriate block size affects the classification results. Using very large block size is unable to discriminate between classes. Therefore, the optimal sized blocks of 16X16 and 8X8 pixels generate acceptable results. Classification can also be performed using support vector machines. The proposed methodology will also be tested on image database created using Bhuvan Geoportal from NRSC, Hyderabad.

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