PCA BASED IMPROVISED CLASSIFICATION OF SATELLITE IMAGE USING RADIAL BASIS CLASSIFIER

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Abstract: The thematic maps has been derived from remotely-sensed images which are precious sources of information for various investigations, it provides spatial and temporal information about the nature of earth surface. It is crucial to understand the different information's gathered with the help of the satellite images. The purpose of this research paper is to classify the IRS P-6(Indian Remote Sensing satellite), which gives LISS-III (Linear Imaging and Self Scanning Sensor) satellite image, by using the PCA (Principle Component Analysis) and the RBC (radial basis classifier). The LISS-III image is the multi-spectral image which has many features used for classification. The multi-spectral images cannot be acknowledged by visual inspection, Hence the remote sensing data has to be classified. Such classification is a difficult task which needs validation of training datasets depending on the algorithm used. Neural networks have shown vast scope for image classification. Here, the pixel based classification method is adopted for the classification of the LISS-III image. A RBF network is a neural network which uses a radial basis function as an activation function; the output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. The radial basis classifier is implemented using the MATLAB. The LISS-III satellite image of Mumbai region is used for training and testing the classifier. In the presented paper the accuracy of classifier is calculated using the confusion matrix and Kappa coefficient, apart from the implementation of the artificial neural network here the different comparative study related to the impact of the number of hidden layers and number of the neurons is also performed.

***Index Terms* - PCA, LISS-III Satellite Image, RBF, Image classification, Classifier.**

I. INTRODUCTION

Satellite images and the thematic maps contain meaningful information for the inventory, monitoring, and management of natural resources the use of remotely sensed images are crucial for regional or global scale studies. With the launch of recent satellites, massive image data are obtained from different sources about the same area. Naturally, each data represents the different features of the area. Using these data may improve the accuracy of classification expressively but then introduces redundancy and requires training data to be used for various purposes. Therefore, new data should be added only if they contribute to an improved classification. In this study, the satellite image has been purposefully used for classification problems. However, it is well known that it is necessary to consider the reflectance features of surface objects varying with the seasonal conditions to improve the accuracy of the classification. PCA is a statistical method; the purpose of PCA used here is to reduce the large dimensionality of the data space (observed variables) to the smaller dimensionality of feature space (independent variables), which are needed to define the data economically. PCA is a dimensionality reduction or data compression method. The PCA can also be used for prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can organize something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system, and control theory, communications etc. The existence of the correlation among the bands of the multispectral image indicates that there is redundancy in the data. In other words, some information is being repeated. It is the repetition of the data between the bands that is reflected in their inter-correlations. The Radial Basis Functions (RBF) emerged as a variant of the artificial neural network. Using RBF functions are embedded in a two-layer neural network, where each hidden unit implements a radial activated function. RBF network is strictly limited to have exactly one hidden layer. This hidden layer can be called a feature vector. The output units represent a weighted sum of hidden unit outputs. The input units in an RBF network is nonlinear while the output is linear. Due to their nonlinear approximation properties, RBF networks are able to model complex mappings, in which perceptron neural networks can only model by means of multiple intermediary layers. In order to use an RBF network we need to specify the hidden unit activation function, the number of processing units, a standard for modeling a given task and training algorithm to find the network parameter.

This work studies the classification of Satellite Image consisting of PCA, whose inputs are the feature of LISS-III image over the principal component into an RBF network acting as a classifier. The main concern is to analyses the accuracy improved using a PCA and RBF classification.

II. STUDY AREA AND CHARACTERISTICS

Here the LISS-III satellite images of Mumbai, Navi-Mumbai and thane regions are used for training and testing purpose. LISS-III is the multispectral satellite image provide by the IRS P6 Indian satellite. The LISS-III satellite image is available in the form of multispectral images in the form of four different bands which are band 2, band 3, band 4 used for vegetation and land use land cover area mapping. LISS-III satellite image is provided by NRSA, Hyderabad, Telangana-500042, and India.

III. CLASSIFICATION ALGORITHMS

3.1 Principal Components Analysis

PCA is a statistical technique used for dimensionality reduction of a data set consisting of many variables correlated with each other, transforms a number of possibly correlated variables into new set of variables called principal components and are uncorrelated variables, ordered such that the retention of variation present in the original variables decreases as we move down in the order[2]. The first principal component represents as much of the variability in the data as possible, and each succeeding component represent as much of the remaining variability as possible. The PCA (Principal Components Analysis) and KL (Karhunen–Loeve) transform are terms often used interchangeably. While they are almost similar, they have important difference is, The Karhunen–Loeve (KL) Transform is the most advanced mathematical algorithm available to achieve both noise filtering and data compression in processing signals of any kind.

The LISS-III images are widely is of value in the analysis of multispectral remotely-sensed data. The transformation of the raw remote sensing data using PCA can result in new component images that may be more interpretable than the original data [1]. Moreover, this technique diminishes influences of noise and error. PCA can be used to diminish the information included in the raw data into two or three bands without mislaying significant information. The principal components analysis can be used for operational classification of land use, color representation or visual interpretation with multi-band data and change detection with multi-temporal data.

3.2 Radial Basis Function

The Radial Basis Functions (RBF) emerged as a variant of artificial neural network. However, their origins are rooted in much older pattern recognition techniques as for example potential functions, clustering, functional approximation, spline interpolation and mixture models. RBF have many properties such as localization, functional approximation, interpolation etc. These properties made them efficiently used in a various applications. It can also be used in various different fields such as: telecommunications signal and image processing control engineering and computer vision used them successfully for various tasks. Finding the RBF weights is called network training. If we have at hand a set of input-output pairs it called training set, we optimize the network parameters in order to give the appropriate network outputs to the given inputs. The network parameter is evaluated by means of a cost function, usually assumed to be the mean square error. After training, the RBF network can be used with data whose underlying data is similar to that of the training set. RBF networks have been effectively applied to a large diversity of applications including chaotic time-series modeling system identification, interpolation, control engineering, electronic device parameter modeling, channel equalization, speech recognition, image restoration, shape from- shading, 3-D object modeling, motion estimation and moving object segmentation, data fusion, etc.

IV. PROPOSED METHODOLOGY

The algorithm is developed in MATLAB 2015. The implementation of proposed method consists of following steps which are as follows:-

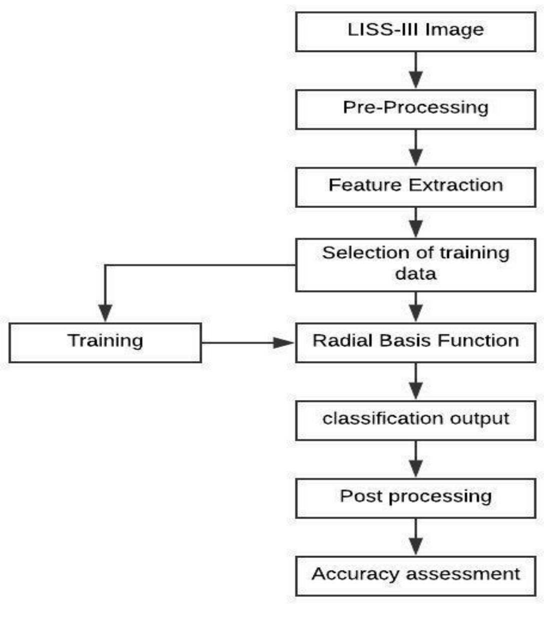

Fig.1 Flow of method

4.1LISS-III image & pre-processing

The LISS-III data is acquired through the website of Bhuvan where data is available for study and research purpose. After the collection of the LISS-III image, it consists of four different bands of images which are band2, band3 band4 and band5. The three red, green and blue bands are selected and after apply low and high pass filter the three images are stacked to form the RGB colour image.

4.2 Feature Extraction and selection of training data

The RGB colour image is used to collect the feature vector for the classification of LISS-III satellite image. The feature vectors of different features are collected using ground truth and google map. Here the red, green and blue colour information of different pixels is collected from different feature sets. The collected feature sets are divided into three different parts which are used for training, testing and validation purpose.

4.3 Applying RBF and PCA

The radial basis neural network in designed for classification purpose. There are two different training sets are prepared one without applying principal component analysis and one after applying principal component analysis algorithm. The radial basis neural network is trained and tested by without PCA algorithm based training set and then again it is trained and tested with PCA applied training data set.

4.4 Classified Image & Post Processing

The implemented methods are then applied on the LISS-III image and its output image collected along with its results and comparative study of both the method. The one with PCA and RBF and other one is without PCA algorithm. The results section clearly specifies the results and comparative results.

IV. RESULTS AND DISCUSSION

The accuracy calculation and assessment is one of the important part of any classification method which is used the calculate performance of algorithm. Here, confusion matrix based method is used to calculate the user's accuracy, producer's accuracy and overall accuracy of the classifier. Here two different tables represent the accuracy assessment of radial basis function and PCA based radial basis function neural network.

Table 4.1: Accuracy assessment of RBF

Class	Water	Land	Forest	Mangroves	Total	User's Accuracy
Water	700	0	0	0	700	100%
Land	12	188	0	0	200	94%
Forest	8	15	276	1	300	92%
Mangroves	6	5	50	209	270	77.41%
Total	726	208	326	210	1470	
Producers Accuracy	96.42%	90.38%	84.46%	99.52%		

Accuracy= (1373/1470)*100
=93.40%

. Table 4.2: Accuracy assessment of PCA+RBF

Class	Water	Land	Forest	Mangroves	Total	User's Accuracy
Water	658	0	0	0	658	100%
Land	0	183	0	0	183	100%
Forest	0	0	268	1	269	99.62%
Mangroves	0	0	1	238	239	99.58%
Total	658	183	269	239	1349	
Producers Accuracy	100 %	100 %	99.62 %	99.58%		

Accuracy= (1347/1349)*100
=99.85%

The above accuracy calculation shows that when only radial basis function neural network is used then it gives the accuracy of 93.40% and when the principal component analysis is applied on the data and then training data is passed to radial basis function for training then its overall accuracy is increased up to 99.85%. The implementation of this different method show that when we are applying PCA on the data and dimensionality of data is reduced then RBF neural network gives good performance result. The LISS-III satellite images are shown below which are before classing and after classing using radial basis function.

Fig.2 False colour image before classification

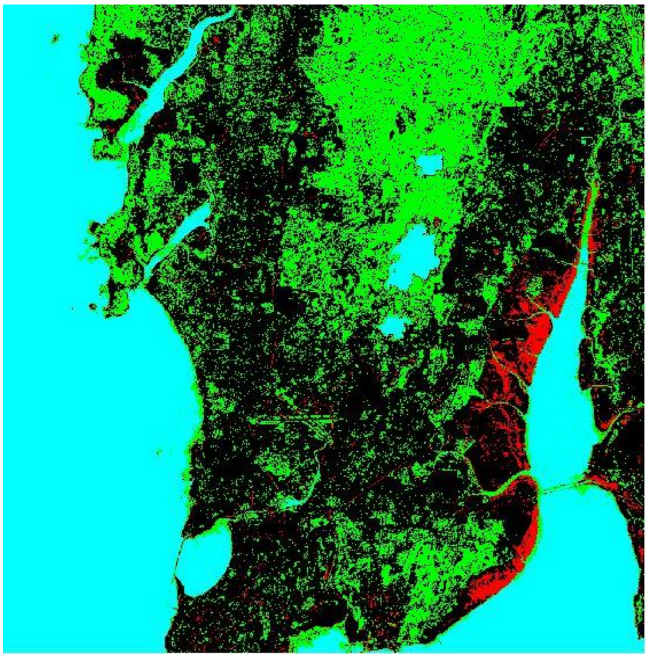

Fig.2 Coloured image after classification

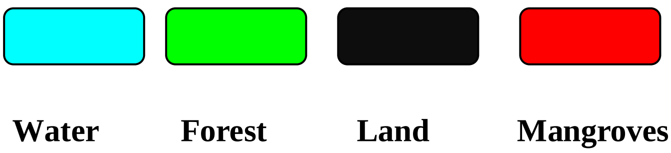

Fig.3 Index

I. CONCLUSION

In this study we have provided an introduction to the Radial Basis Function Networks for the classification of Satellite image LISS-III. The proposed method consist of two different ways of implementing radial basis function one with PCA and other without PCA. The accuracy assessment of both the method show that accuracy of only radial basis function is less than PCA based radial basis function neural network. The results show that if data are huge and large in size then it takes more time for training and accuracy of classifiers also degraded and if the dimensionality of data is reduced then then time and accuracy of classifiers improved. In future the time of execution of classifiers also calculated and based on that some combination of classifiers or data reduction techniques can be suggested.

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