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Comparison of Supervised Classification Methods On Remote Sensed Satellite Data: An Application In Chennai, South India

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Abstract: ***This paper presents classification of various land cover types from the raw satellite image using supervised classifiers and performances of the classifiers are analyzed. Geo coded and Geo-referenced remote sensed images from Survey of India, Government of India Topographical maps are used. Prior to classification, Training process to assemble a set of statistics describing spectral response pattern of each land cover type is done. The quality of training plays a crucial role in success of classification. Classification is executed based on the spectral features using Minimum distance to mean classifier, Maximum likelihood classifier and Mahalanobis classifier. Efficiency of Classification results are assessed by using accuracy assessment and Confusion matrix. Performance of Maximum likelihood classifier is found to be better than other two. ERDAS IMAGINE 9.2, the world's leading geospatial data authoring software is used.***

Keywords: Spectral features,remote sensing, Minimum distance to mean classifier, Maximum likelihood classifier, Mahalanobis classifier, Accuracy assessment, confusion matrix, ERDAS IMAGINE 9.2

1. Introduction

Remote sensing refers to the use of aerial sensor technologies to detect and classify objects on Earth (both on the surface, and in oceans and atmosphere) by means of propagated signals .Remote sensing affords us the capability to literally see the invisible. From remote sensing's aerial or space vantage point we can obtain a synoptic view of earth resources. Present scenario gives more importance to digital image representing information related to remote sensing, medical areas, geology, and oceanography, land use, agriculture etc. The information about these digital images reveal is of greater importance to decision makers and for further research. The image captured so consists of scan lines and pixels termed as spectral image. Each pixel carries unique information. Image acquired by remote sensing satellites are useful in tracking of resources within the earth, geographical mapping, prediction of the growth of agricultural crops, urban growth, weather, flood, fire, environmental conditions and so on.

A generalized satellite image classification and analysis steps shown in fig 1, is to procure LANDSAT satellite image, training stage by assembling the information, identifying land cover types, Classification and verifying the accuracy of the results obtained.

The aim of this work is identification of connection between unknown pixels with land cover types of known spectral patterns and assigned it to most similar category.

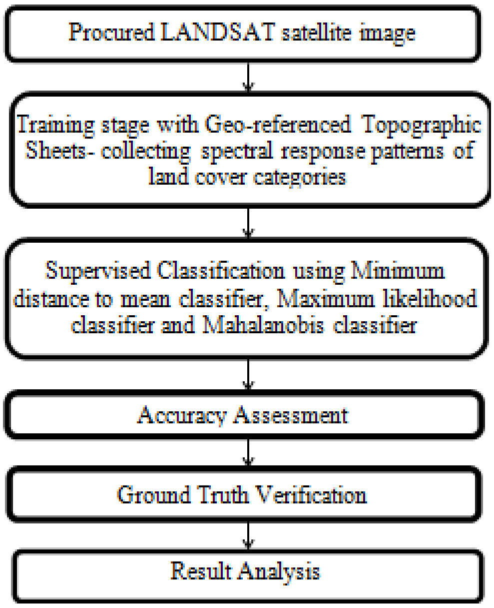

Figure 1: Satellite image classification and analysis steps

There exist various classification methods for classifying satellite image which includes Maximum Likelihood Classifier (MLC), K Nearest Neighborhood Classifier (K-NN), K-means classifier, and parallelepiped classifier, Minimum Distance to means Classifier (MDC), Decision Tree classifier, Artificial Neural Network Classifier (ANN) and fuzzy classifier. RatikaPradhan, Ghose M.K and Jeyaram A. have suggested k-means for unsupervised classification and Bayesian classifier for supervised classification of satellite image [15]. ManishaB.Patil, Chitra G. Desai and BhuvanaN. Umrikarhave performed image analysis on raw data using Maximum Likelihood Classifier and Minimum Distance method [10].

Ramanathan Sugumaran has suggested Artificial Neural Network and Maximum Likelihood Classifier for different land cover classification [14]. Victor Chukwuemeka, Godwin Uchechukwu and John Okwor has suggested about assessing and analyzing urban development using object based classification of a remotely sensed satellite image in their paper [17]. Marcal A.R.S, Borges J.S, Gomes J.A and Pinto Da Costa J.F has carried out supervised classification of a multispectral image from the Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER) sensor [11].

Rajesh K Dhumal, YogeshRajendra, Kale K.V, Mehrotra S.C has done crop classification in supervised as well as unsupervised methods [13]. Adam Collingwood, Steven E. Franklin et al. has done three different object-based classification methods (one unsupervised and two supervised methods) on agricultural and herbaceous land cover on the regions of Western Alberta [1]. Al-Ahmadi F.S. and Hames A.S. has utilized RS technologies to extract LULC from satellite images for remote arid areas in Saudi Arabia. Here they used four different classifications and they found that MLC has given the best results [2].

Perumal K and Bhaskaran R have proved that Mahalanobis classifier outperforms even advanced classifiers. They also showed the importance of considering the dataset-classifier relationship for successful image classification [12]. Subhash Thakur, Akhilesh Singh et al. have used different satellite image classification methods and their results were compared using the satellite images of Jabalpur district. They used ERDAS IMAGINE software tool and also proved that MLC is more applicable and reliable [16].

Jwan Al-Doski, Shattri B. Mansorl has handled the different components related to image classification techniques such as K-means classifier and SVM [8]. Jojene R. Santillan has approached the method of applying the MLC to a combination of multi-source data sets that shows potential in mapping Sago palms in the areas of Philippines [7].

Rest of the paper is organized in the following manner. Section II gives some background information on procured satellite images. Section III describes the training process. In Section IV, supervised classification methods which are assessed are presented. Section V deals with accuracy assessment using confusion matrix and kappa coefficient.Section VI presents experimental methodologies and results using ERDAS IMAGINE tool

1.1 Procured Satellite Image

Satellite images of Chennai metropolitan area which lies between 13°1’N latitude 80°20’E longitude are taken. The extent of the geographical area is covered by SOI topographic maps 66 c/4 and c/8. Path-row is 142-51 geocoded. The study area is characterized by the presence of major features such as roads, railway lines, urban with vegetation, urban without vegetation, water bodies, forest areas and stadium. The remote sensed satellite image of the study area is shown in fig 2. The study area image is captured by LANDSAT. This False Color Composite (FCC)[20] image consists of spectral bands 2, 3, 4 which bring about various information’s about Chennai city. Hence it is called multispectral image.

They record green, red and infrared. The result is a False Color Composite image (FCC) in which blue images result from objects reflecting primarily green energy, green images result from objects reflecting primarily red energy and red images results from objects reflecting primarily infrared portion of EM spectrum. The raw image of Chennai city does not signify the various features like road, river, beach, ocean, land use, urban with vegetation, urban without vegetation. Hence this raw data so obtained has to be properly classified so as to obtain optimal information.

Figure 2: LANDSAT FCC image of Chennai, Tamilnadu

2. Training Stage

Training data of known identity is used to classify pixels fo unknown identity. The overall objective of the training process is to assemble a set of statistics that describe the spectral response pattern for each land cover type to be classified in an image. It is during the training stage that the size, shape, location and orientation of the “cloud of points” for each land cover class are determined.

The image analyst must develop training statistics for all spectral classes constituting each information class to be discriminated by the classifier. For example, in a final classification output, one might wish to delineate an information class called “forest”. If the image under analysis contain only one forest body and if it has uniform spectral response characteristics over its entire area, then only one training area would be needed to represent the forest class. If, however, the same forest body contains distinct areas of sparse and dense regions, a minimum of two spectral classes would be required to adequately train on this feature. If multiple forest bodies occurred in the image, training statistics would be required for each of the spectral classes that is present in the forest areas.

The location of training areas in an image is normally distributed by viewing windows, or portions of the full scene, in an enlarged format on an interactive color display device. The image analyst normally obtains training sample data by outlining training areas using a reference cursor. Figure 3 shows the boundaries of several training site polygons that have been delineated in this manner. Note that these polygons have been carefully located to avoid pixels located along the edges between land cover types. The row and column coordinates of the vertices for these polygons are used as the basis for extracting (from the image file) the digital numbers for the pixels located within each training area boundary. These pixel values then form the sample used to develop the statistical description of each training area (mean vector and covariance matrix in case of maximum likelihood classifier).

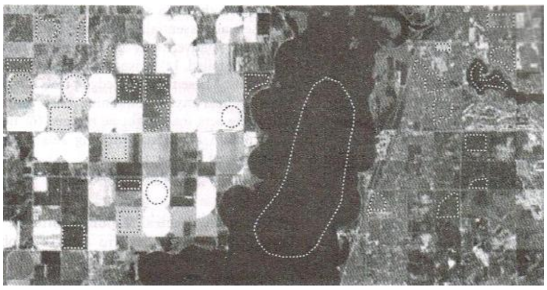

Figure 3: Training area polygons delineated on a monitor

When delineating training set pixels, it is important to analyze several training sites throughout the scene. For example, it would be better to define the training pattern for a given class by analyzing 20 locations containing 40 pixels of a given type than one location containing 800 pixels. Dispersion of the sites throughout the scene increases the chance that the training data will be representative of all the variations in the cover types present in the scene.
One does not want to omit any important spectral classes occurring in a scene, but one also does not want to include redundant spectral classes in the classification process from a computational standpoint. During the process of training set refinement the analyst attempts to identify such gaps and redundancies.

As part of the training set refinement process, the overall quality of the data contained in each of the original candidate training areas is assessed and the spectral separability between the data sets is studied. The analyst carefully checks to see if all data sets essentially normally distributed and spectrally pure. Training areas that inadvertently include more than one spectral class are identified and recompiled. Likewise, extraneous pixels may be deleted from some of the data sets. These might be edge pixels along agricultural field boundaries or within-field pixels containing bare soil rather than the crop trained upon. Training sets that might be merged are identified, and the need to obtain additional training sets for poorly represented spectral classes is addressed.

2.1 Classifiers

The classification of remotely sensed data is used to assign corresponding levels with respect to groups with homogeneous characteristics, with the aim of discriminating multiple objects from each other within the image. Classification will be executed on the base of spectral or spectrally defined features. Each unknown pixel is compared to the spectral response pattern and assigned a class which are most similar in category. Techniques for classification [21] which are to be analyzed are

A. Minimum distance to Mean Classifier

The minimum distance classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi feature space. The distance in Equation 1 is called index of similarity.

$d_k^2 = (X-\mu_k)^T (X-\mu_k)$ ----------Eqn (1)

WhereX is vector of image data

$\mu_k$is the mean vector of the k^{th} class

It is same as the Euclidean distance between two vectors. The minimum distance classifier is not complete, as it does not take correlations with in dataset.

B. Mahalanobis distance classifier

Mahalanobis distance is a distance measure between two points in the spacedefined by two or more than two correlated variables. That is, Mahalanobisdistancetakes the correlations within a data set between the variable into consideration. Ifthere are two non-correlated variables, the Mahalanobis distance between thepoints of the variable in a 2D scatter plot is same as Euclidean distance.

In mathematical terms, the Mahalanobis distance is equal to the Euclidean distancewhen the covariance matrix is the unit matrix. This is exactly the case then if the two columns of the standardized data matrix are orthogonal. The Mahalanobis distance depends on the covariance matrix of the attribute and also accounts for the correlations. To say exactly, the covariance matrix is utilized to correct the effects of cross-covariance between two components of random variable.

The Mahalanobis distance is the distance between an observation and the center for each group in m-dimensional space defined by m variables and their covariance. Thus, a small value of Mahalanobis distance increases the chance ofan observation to be closer to the group's center and the more likely it is to beassigned to that group.

For each feature vector, the Mahalanobis distances towards class means are calculated as in Equation 2. This includes the calculation of the variance-covariance matrix V for each class.

. The distance in Equation 1 is called index of similarity.

$d_k^2 = (X-\mu_k)^T \mathbf{V} (X-\mu_k)$ ----------Eqn (2)

Where X is vector of image data $\mu_k$is the mean vector of the kth class **V**is the variance covariance matrix

C. Maximum Likelihood classifier:

The Maximum Likelihood Classifier quantitatively evaluates both the varianceand covariance of the category spectral response patterns when classifying an unknown pixel. To do this, an assumption is made that the distribution of the cloud of points forming the category training data is Gaussian(normal distribution). This assumption is generally reasonable for common spectral response distributions. Under the assumption, the distribution manner of a category response pattern can be completely described by the mean vector and the covariance matrix. Given these parameters,we may compute the statistical probability of a given pixel value being a member of a particular land cover class. Figure 4 shows the probability values plotted in a three dimensional graph. The probability density functions (Eqn. (3)) are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category

$$\hat{p}(x \mid w_i) = \frac{1}{(2\pi)^{\frac{1}{2}} \hat{\sigma}_i} \exp\left[-\frac{1}{2} \frac{(x - \hat{\mu}_i)^2}{\hat{\sigma}_i^{\,2}} \right]$$ ….. Eqn(3)

The probability density functions (Eq. (3)) are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. That is, the computer would calculate the probability of the pixel value occurring in the distribution of class “corn”, then the likelihood of its occurring in class “sand”, and so on. After evaluating the probability in each category, the pixel would be given to the most likely class or be labelled “unknown” if the probability values are all below a threshold set by the analyst.

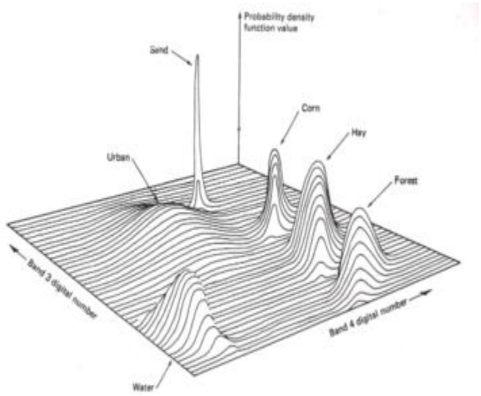

Figure 4: Probability density functions defined by maximum likelihood classifiers

Accuracy Assessment

Accuracy assessment is a general term for comparing the classification to geographical dataproviding the assumptions are true, so as to determine the accuracy of the classification process. The cell array for this utility lists twoset of class values for the randomly selected points (random points) in the classified image file. One set of class values is automatically assigned to these random points as they are selected, and the other set of class values (referencevalues) is made as ourinput. The reference values of these data should be based on ground truth data values, previously tested maps, or other data like aerial photos.

D. Confusion Matrix

One of the most common means of expressing classification accuracy is the preparation of a classification error matrix. It’s called a confusion matrix or a contingency table. In a confusion matrix, classification results are compared to additional ground truth information. It identifies the nature of the classification errors, as well as their quantities. Fig 5 illustrates the concept of confusion matrix.

		prediction outcome		
		p	n	total
actual value	p'	True Positive	False Negative	P'
	n'	False Positive	True Negative	N'
	total	P	N	

Figure 5: Representation of confusion matrix

Use a confusion matrixis to show the accuracy of a classification result by comparing a classification result with ground truth information. In each case, producer and user accuracies, an overall accuracy, kappa coefficient are reported. Use a Ground Truth Imageis to calculate an error mask images for each class showing which pixels are incorrectly classified. Overall Accuracy is calculated by summing the number of pixels classified correctly and dividing by the total number of pixels.

E. Kappa Coefficeint

Kappa Coefficient (k) is another measure of the accuracy of the classification. It’s calculation is done by multiplying the total number of pixels in all the ground truth classes (N) by the sum of the diagonals of the confusion matrix, subtracting the sum of the ground truth pixels in a class times the sum of the classified pixels in that class summed up over the all classes, and dividing it by the total number of pixels squared minus the sum of the ground truth pixels in that class times the sum of the classified pixels in that class summed over all classes.

3. Experimental Methodologies and Results

ERDAS IMAGINE performs advanced remote sensing analysis and spatial modelling to create new information. For supervised classification, training is done and Signature identification is performed, where each class is given a unique color. Image is imported, false color composite is allocated and required area is cropped. Three types of supervised classifiers, Minimum distance, Mahalanobis and Maximum likelihood distance classifier are selected, and the classification outputs are given in Figure 6.

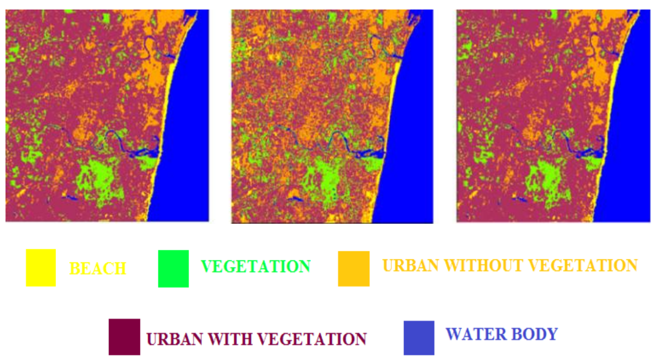

Figure 6: Classification results of MLC, MDC and Mahalanobis classifiers

Error matrix is given in Table I and the overall accuracy and Kappa coefficients of each class corresponding to given three supervised classifiers are given in table II.

Table 1: Error Matrix

Data	U	B	V	UWV	UV	W	Row Total
U	0	0	0	0	0	0	0
B	0	1	0	0	0	0	1
V	0	0	4	0	0	0	4
UWV	0	0	0	4	0	0	4
UV	0	0	1	3	25	1	30
W	0	0	0	0	0	11	11
Col Total	0	1	5	7	25	12	50

Table 2: Assessment Results

Classifiers	*Overall Classification Accuracy*	*Overall Kappa Statistics*
Maximum Likelihood classifier	93.33%	0.92
Minimum Distance to Mean classifier	85.72%	0.82
Mahalanobis classifier	90.00%	0.84

4. Conclusion

Five LULC categories were recognized in the study area namely Beach, Vegetation, Urban with vegetation, Urban without vegetation, Water body. In the classification stage, three supervised classification methods were selected to classify the images. The three methods are Minimum Distance classifier, Mahalanobis classifier and Maximum Likelihood classifier was performed to the images. Accuracy assessment was done finally to compute the probability of error for the classified map. A total of 70 randomly sample (for accuracy assessment random points were collected from reference image with classified images) Points were chosen for accuracy assessment. Three measures of accuracy were tested in this study namely overall accuracies, confusion or error matrices and kappa coefficients. Maximum Likelihood produced the highest accuracy with overall accuracy of 93.33%. Then followed byMahalanobis gave the overall classification accuracy of 90.00%and Minimum distance showed the overall classification accuracy of 85.72%.

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