Class Quantification of Aerial Images using Maximum Likelihood Estimation.

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***Abstract*— Class quantification of aerial images plays a vital role in remote sensing. One of the class quantification method is discussed in this paper. Proposed method uses Maximum Likelihood Estimation based classifier for class quantification. Algorithm is trained by the sample classes derived from parent image. Feature space is estimated from each training sample. Different classes are labeled in test image by maximizing the likelihood function. The experimentation is done on aerial images obtained by Geo eye satellite at the elevation of 0.6km. The percentage area covered by the labeled classes is computed for all test images.**

Keywords—class quantification; parameter estimation; Maximum Likelihood Estimation.

I. Introduction

Remote sensing is becoming more and more powerful as the numbers of pattern classification techniques are being developed. Development in the satellite imaging since last decade has shown tremendous improvement in accuracy and the reliability of remote sensing and application like aerial image classification. Many pattern classification techniques have proven their significant place in the aerial land cover classification. Theory of such classifiers has been extensively studied and evolved since last two decades. Maximum Likelihood (ML) is one such parameter estimation and classification technique that falls under supervised machine learning approaches. We discuss use of same for class quantification of aerial images. Various statistical approaches for pattern recognition, classification, clustering and feature extraction are extensively discussed by jain *et al* [1]. Bag-of-Visual Words (BOV) for object based classification is described by Sheng *et al* [6]. A tutorial exposition on maximum likelihood estimation (MLE) and use of MLE for statistical modeling is thoroughly discussed by Myung [3]. Scattering mechanism classification of polarimetric synthetic aperture radar (PolSAR) images is given by Cheng *et al* [7]. Generalized method for computing ML estimates from incomplete data is presented by Dempster *et al* [2].

II. Overview

We used maximum likelihood classification method to classify the versatile land cover type present in the aerial images. In general we classify various features or land cover types represented by homogeneous group of pixels identified in the image. In supervised classification we select these groups of pixel which is homogeneous in nature as the training samples to train the classifier.

In the first section of this letter maximum likelihood method, its optimal properties and the associated discriminant function is discussed. Later on the algorithm of Maximum Likelihood classification with its overall flow is given to get the deeper understanding of the concept in section two. The last part of the paper talks about detailed experimentation and the result of quantification for different aerial images.

A. Maximum Likelihood Estimation.

In Maximum Likelihood Classifier pixel is assigned to the class of which its likelihood value is maximum. Following are some unique properties of ML estimator in order to prove its superiority.

- Consistency: one can recover the true parameter value asymptotically.
- Parameterization invariance: though we use different parameterization we get the same MLE solution.
- Efficiency: we get least achievable variance of the parameter estimated.
- Sufficiency: ML estimator gives whole information of the parameter.

ML classifier uses training data to estimate the mean and the variance of each class and it is derived from the Bayes theorem which states that a posteriori probability that the pixel with the feature vector x is given by

$$P(\omega_j|x) = \frac{P(x|\omega_j)P(\omega_j)}{P(x)} \quad (1)$$

Where $P(\omega_j)$ is the priori probability, $P(\omega_j|x)$ posterior probability i.e. the probability of class being ω_j with the feature value x , $p(x|\omega_j)$ is the likelihood of ω_j with the feature value x.
For d category Likelihood is given by

$$P(\omega_j) = \sum_1^d P(\omega_j|x) \quad P(x) \quad (2)$$

Where j=1 to d and d is number of classes.
Pixel x belongs to class ω_i if $P(\omega_i|x) > P(\omega_j|x)$.

The log likelihood or the (discriminant function) given by,

$$g_i(x) = ln\, P(\omega_i|x) = -\frac{1}{2}(x-\mu_i)^t\ \Sigma_i^{-1}(x-\mu_i) - \frac{d}{2} ln\, 2\pi - \frac{1}{2}\ ln\, |\Sigma_i| \quad (3)$$

Where $\Sigma \equiv \varepsilon[(x-\mu)(x-\mu)^t]$

Pixel x belongs to the class ω_i if $g_i(x) > g_j(x)$

B. Methodology

Following are the some basic steps to be followed in ML classifier.

1) Number of category is determined on the basis of homogeneous group of pixels .i.e. In how many land cover types the given image can be classified.

2) The training pixel selection

a) Size: the size of the training sample should be enough in size so that it can give sufficiently accurate information about the class.

b) Shape: shape is not much important, but regular shape like pentagon and square etc are used.

c) Number of training areas: Depends on the number of classes the given images has to be classified the numbers of training areas are selected. Generally five to ten training sample for each class is selected in order to get the special variability of the information.

d) Placement: the training area should be placed in such a way that it does not lie close to the edge of the boundary of the information class.

e)Uniformity: this is one of the most important characteristics regarding the training samples. The training sample should be selected in such a way that they should be uniform in nature.

III.

The location used to study is Sillod, located in Aurangabad(MH) district India, around the longitude 75º.65' E and latitude 20º.3' N .The images were taken from Geo eye satellite at the height of 0.6 km. The study area is shown in the world map *figure 2* .In this case we have classified the images in four main categories viz-farm, soil, bare land and buildings. Training pixels for each category were selected by placing a square in that particular land cover type. The most important consideration while placing these squares was the uniformity and how well they represent that class throughout the image. From these training pixels the mean and variance of each category were estimated and these parameters were used by ML Classifier to classify each pixel of test image in said categories.

C. Algorithm

The selection of the training data for each class is carried out at the very first stage. The applied selection procedure is described in methodology section of this paper. Derived training samples are used to train the ML classifier, by estimating parameters like mean and variance using normal ML Estimator. These estimated parameters are the key elements in the Maximum Likelihood classifier. Further the discriminant function based on estimated parameters helps to classify each pixel of the input test image in order to assign it to the true class. The associated discriminant function is given by equation (3). The overall flow of proposed method is as given in figure 1.

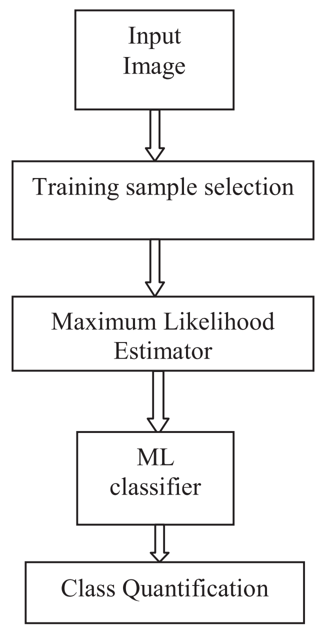

Fig. 1. Flow chart of algorithm

III. EXPERIMENTATION AND RESULTS

The result of the Maximum Likelihood Classifier is shown in the *figure 3*. The *figure 3.(a)* is an input image given to the classifier to categories it in to four different classes that are Farm ,Soil ,Bare land and the buildings. These four major categories are mainly identified in the study area. *Figure 3.(b)* shows the output of the Maximum Likelihood Classifier. Four classes are shown in four different colors Farm (Green), Soil (Brawn), bare land (Saffron) and the buildings (Yellow). For the further analysis four images are classified using the ML Classifier and k mean clustering. The result of this experiment is tabulated in table number I, percentage of each class is shown in the table. These eight images were taken from same height and with the same resolution but each of these images contain different land cover percentage. One can see that the percentage of these classes are different for different images; as this study area comes under rural part the percent of building cover is very less.

Fig .2 location of the study area.

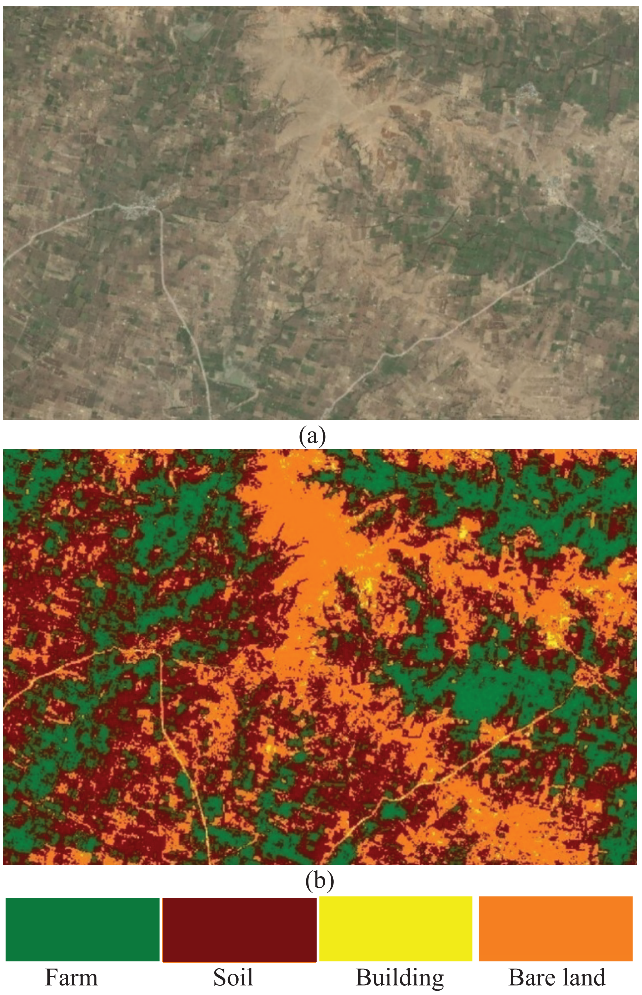

Fig.3. (a) Test image 7 from Image set (Height 0.6Km)
(b) Output of Maximum Likelihood Classifier.

TABLE I COMPARISION OF RESULT OBTAINED BY MLE AND K MEAN

Test Images	Classes (In percentage)				
		Farm	Soil	Bare land	Buildi-ngs
Image9	MLE	25.48	46.52	27.15	0.83
	Kmean	17.10	52.05	30.78	0.06
Image10	MLE	30.09	43.10	24.29	0.25
	kmean	13.78	57.06	28.89	0.24
Image11	MLE	23.99	39.24	34.25	2.50
	kmean	15.13	49.45	35.33	0.07
Image12	MLE	26.61	48.16	26.53	0.97
	kmean	16.28	52.06	31.58	0.06

IV. CONCLUSION

The study area consists of the four main land cover type which were sufficient to categorize the image. The Maximum Likelihood Classifier model developed for this study area worked very well and classified each pixel to its proper class. The results of quantified classes in captured test images are given in table I. The main concern while designing the model was selection of proper area which uniformly describe the particular class throughout the image. This proper selection is one of the main factors that can lead to the high accuracy of the Classifier.

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