Classification of crops and analyzing the acreages of the field

Darpan Madia[1], Dhaval Bhanushali[2], Suyash Bane[3], Prof. Shyamal Virnodkar[4], Prof. Vricha Chavan[5]

[1,2,3] K.J Somaiya Institute of Engineering and Information Technology, Mumbai
[4]Professor, Dept. of Computer Engineering, K.J Somaiya Institute of Engineering and Information Technology, Maharashtra, India
[5]Professor, Dept. of Electronics Engineering, Veermata Jijabai Technological Institute, Maharashtra, India

---

Abstract- *Agriculture is considered to be backbone of Indian economy with nearly 70% of population depends on agriculture. In India, precision agriculture and sustainable agriculture and development are becoming popular with the application of latest technologies available in the field and active research in agriculture by using satellite images for various agricultural applications. Thus use of satellite images for identification, classification and estimation of yield carries a lot of importance. Such studies are growing across the world in recent years.In India, several studies are done to classify crops, but still requires more research on different crops. Thus the growth patterns of crops and the approximation of the yields of the crops which particularly with industrial applications would help farmers, government and industries.. The main motto is to help the farmers, Government and industry to carry out such studies.*

Keywords: **Maximum Likelihood, Sugarcane, satellite images, Landsat, NDVI, GNDVI, Confusion Matrix.**

Introduction:

Sugarcane is the most important perennial crop planted in many countries like brazil india and china . India has largest area under sugarcane cultivation in the world and is the worlds second largest producer of sugarcane.the leading producer of sugarcane stands brazil . Bagasse, the crushed cane residue, can be more beneficially used for manufacturing paper instead of using it as fuel in the mills. It is also an efficient substitute for petroleum products and a host of other chemical products.

Conditions of Growth:

It has a long duration of crop growth and requires 10 to 15 and sometimes even 18 months to mature, depending upon the geographical conditions. It requires hot and humid climate ranging from a average temperature of 21°-27°C and 75-150 cm rainfall.

Image Classification

Image classification refers to the computer-assisted interpretation of remotely sensed images. Although some procedures are able to incorporate information about such image characteristics as texture and context, the majority of image classification is based solely on the detection of the spectral signatures (i.e., spectral response patterns) of land cover classes. The success with which this can be done will depend on two things.

1) The presence of distinctive signatures for the land cover classes of interest in the band set being used.

2) The ability to reliably distinguish these signatures from other spectral response patterns that may be present.

There are two general approaches to image classification, Supervised and unsupervised. They differ in how the classification is performed. In the case of supervised classification, the software system delineates specific land cover types based on statistical characterization data drawn from known examples in the image (known as training sites). With unsupervised classification, however, clustering software is used to uncover the commonly occurring land cover types, with the analyst providing interpretations of those cover types at a later stage.

Supervised Classification

The first step in supervised classification is to identify examples of the information classes (i.e., land cover types) of interest in the image. These are called “Training Sites”. The software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called Signature Analysis and may involve developing a characterization as simple as the mean or the range of reflectances on each band, or as complex as detailed analyses of the mean, variances and covariance over all bands.

Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectances for each pixel and making a decision about which of the signatures it resembles most. There are several techniques for making these decisions, called classifiers.

Hard Classifiers

The distinguishing characteristic of hard classifiers is that they all make a definitive decision about the land cover class to which any pixel belongs, Mainly there are three supervised classifiers in this group: Parallelepiped, Minimum Distance to Means, and Maximum Likelihood.[2] They differ only in the manner in which they develop and use a statistical characterization of the training site data. Of the three, the Maximum Likelihood procedure is the most sophisticated, and is the most widely used classifier in the classification of remotely sensed imagery.

Soft Classifiers

Contrary to hard classifiers, soft classifiers do not make a definitive decision about the land cover class to which each pixel belongs. Rather, they develop statements of the degree to which each pixel belongs to each of the land cover classes being considered. Thus, for example, a soft classifier might indicate that a pixel has a 0.72 probability of being forest, a 0.24 probability of being pasture, and a 0.04 probability of being bare ground. A hard classifier would resolve this uncertainty by concluding that the pixel was forest. However, a soft classifier makes this uncertainty explicitly available, for any of a variety of reasons. For example, the analyst might conclude that the uncertainty arises because the pixel contains more than one cover type and could use the probabilities as indications of the relative proportion of each. This is known as Sub-Pixel classification. Alternatively, the analyst may conclude that the uncertainty arises because of unrepresentative training site data and therefore may wish to combine these probabilities with other evidence before hardening the decision.

Many software offer different soft classifiers. The difference between them relates to the logic by which uncertainty is specified—Bayesian, Dempster-Shafer, and Fuzzy Sets are some of them.

Unsupervised Classification

In contrast to supervised classification, where we tell the system about the character (i.e., signature) of the information classes we are looking for, unsupervised classification requires no advance information about the classes of interest. Rather, it examines the data and breaks it into the most prevalent natural spectral groupings, or clusters, present in the data. The analyst then identifies these clusters as land cover classes through a combination of familiarity with the region and ground truth visits.

The logic by which unsupervised classification works is known as Cluster Analysis, which performs classification of composite images that combine the most useful information bands.[1] It is important to recognize, however, that the clusters unsupervised classification produces are not information classes, but spectral classes (i.e., they group together features (pixels) with similar reflectance patterns). It is thus usually the case that the analyst needs to reclassify spectral classes into information classes. For example, the system might identify classes for asphalt and cement which the analyst might later group together, creating an information class called pavement.

While attractive conceptually, unsupervised classification has traditionally been hampered by very slow algorithms. However, the clustering procedure provided in some software like IDRISI is extraordinarily fast and can thus be used iteratively in conjunction with ground truth data to arrive at a very strong classification. With suitable ground truth and accuracy assessment procedures, this tool can provide a remarkably rapid means of producing quality land cover data on a continuing basis.

In addition to the above mentioned techniques, two modules bridge both supervised and unsupervised classifications. There is a procedure known as ISODATA, iteratively Self Organising Cluster Analysis to classify up to 7 raw bands with the user specifying the number of clusters to process. The procedure uses module to initiate a set of clusters that seed an iterative application of Maximum likelihood like procedure, each stage using the results of the previous stage as the training sites for this supervised procedure. The result is an unsupervised classification that converges on a final set of stable members using a supervised approach (hence the notion of "self-organizing"). In another method, the procedure starts with training sites that characterize individual classes, but it results in a classification that includes not only these specific classes, but also significant (unknown) mixtures that might exist. Thus the end result has much the character of that of an unsupervised approach.

The classification can be done by using Geographical Information System software such as ARCGIS, QGIS, GRAM++, IDRISI etc which has inbuilt procedures for different classification algorithms. The classification can also be done by using Artificial Neural Networks such SVM, Decision Tree classifiers, Back Propagation neural networks etc. Genetic algorithm based procedures are also used for classification.

Remote sensing :

Remote sensors collect data by detecting the energy that is reflected from Earth. These sensors can be on satellites or mounted on aircraft.

Remote sensors can be either passive or active. Passive sensors respond to external stimuli. They record natural energy that is reflected or emitted from the Earth's surface. The most common source of radiation detected by passive sensors is reflected sunlight.

In contrast, active sensors use internal stimuli to collect data about Earth. For example, a laser-beam remote sensing system projects a laser onto the surface of Earth and measures the time that it takes for the laser to reflect back to its sensor.

Landsat :

The Landsat 8 satellite images the entire Earth every 16 days in an 8-day offset from Landsat 7.[3] Data collected by the instruments onboard the satellite are available to download at no charge from EarthExplorer, GloVis, or the LandsatLook Viewer within 24 hours of acquisition.

Landsat 8 measures different ranges of frequencies along the electromagnetic spectrum – a color, although not necessarily a color visible to the human eye. Each range is called a band, and Landsat 8 has 11 bands. Landsat numbers its red, green, and blue sensors as 4, 3, and 2, so when we combine them we get a true-color image .

An alternative to the model-based approach is to define classes from the statistics of the image itself. The classes are defined by an operator, who chooses representative areas of the scene to define the mean values of parameters for each recognizable class (hence it is a "supervised" method). A probabilistic approach is useful when there is a fair amount of randomness under which the data are generated. Knowledge of the data statistics (i.e. the theoretical statistical distribution) allows the use of the Bayes maximum likelihood classification approach that is optimal in the sense that, on average, its use yields the lowest probability of misclassification[1]

After the class statistics are defined, the image samples are classified according to their distance to the class means. Each sample is assigned to the class to which it has the minimum distance. The distance itself is scaled according to the Bayes maximum likelihood rule.

Bayes classification for polarimetric SAR data was first presented in 1988 . The authors showed that the use of the full polarimetric data set gives optimum classification results. The algorithm was only developed for single-look polarimetric data, though. For most applications in radar remote sensing, multi-looking is applied to the data to reduce the effects of speckle noise. The number of looks is an important parameter for the development of a probabilistic model.

The full polarimetric information content is available in the scattering matrix S, the covariance matrix C, as well as the coherency matrix T. It has been shown that T and C are both distributed according to the complex Wishart distribution . The probability density function (pdf) of the averaged samples of T for a given number of looks, n, is

$$P_T^{(n)}(<T>) = \frac{n^{qn} |<T>|^{n-q} e^{(-nTrace(V^{-1}<T>))}}{K(n,q)|V|^n}$$

where:

- **<T>** is the sample average of the coherency matrix over n looks,
- **q** represents the dimensionality of the data (3 for reciprocal case, else 4),
- **Trace** is the sum of the elements along the diagonal of a matrix,
- **V** is the expected value of the averaged coherency matrix, E{<T>}, and
- **K(n,q)** is a normalization factor.[4]

To set up the classifier statistics, the mean value of the coherency matrix for each class Vm must be computed

$$V_m = E\{<T> \mid <T> \epsilon\ \omega_m$$

where ωm is the set of pixels belonging to class m in the training set.[4]

According to Bayes maximum likelihood classification a distance measure, d, can be derived :

$$d(<T>, V_m = n\,(ln|V_m| + Trace(V_m^{-1} <T>)) - ln(P(\omega_m))$$

where the last term takes the a priori probabilities P(ωm) into account. Increasing the number of looks, n, decreases the contribution of the a priori probability. Also, if no information on the class probabilities is available for a given scene, the a priori probability can be assumed to be equal for all classes. An appropriate distance measure can then be written as :

$$d(<T>, V_m = ln|V_m| + Tracce(V_m^{-1} <T>)$$

which leads to a look-independent minimum distance classifier:

$$d(\{T\}, V_m) \le d(\{T\}, V_j)\ for\ all\ \omega \ne \omega_m$$

Applying this rule, a sample in the image is assigned to a certain class if the distance between the parameter values at this sample and the class mean is minimum.[4] The look-independence of this scheme allows its application to multi-looked as well as speckle-filtered data . This classification scheme can also be generalized for multi-frequency fully polarimetric data provided that the frequencies are sufficiently separated to ensure statistical independence between frequency bands

The classification depends on a training set and must therefore be applied under supervision. It is not based on the physics of the scattering mechanisms, which might well be considered a disadvantage of the scheme.[6]However, it does utilize the full polarimetric information and allows a look-independent image classification.

Note that the covariance matrix can also be used for this type of Bayes classification. The coherency matrix was chosen for the simple reason of compliance with the H / A / α-classifier described in the previous section.

Accuracy in maximum likelihood:

Accuracy assessment of the ML classification was determined by means of a confusion matrix (sometimes called error matrix), which compares, on a class by class basis, the relationship between reference data (ground truth) and the corresponding results of a classification .

Producer accuracy is a measure of the accuracy of a particular classification scheme and shows the percentage of a particular ground class that is correctly classified. It is calculated by dividing each of the diagonal elements in Table by the total of each column respectively.

The minimum acceptable accuracy for a class is 90% shows the producer for all the classes. It is obvious that all classes possess producer accuracy higher than 90%.

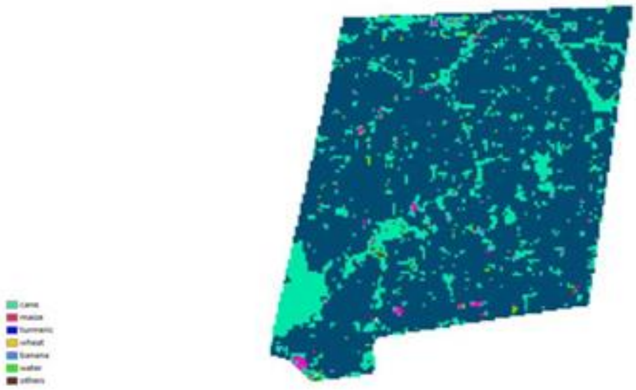

Fig I. Classified image of Handigund village

Crop Health:

Chlorophyll is a major component of many cell ingredients and plays an important role in several physiological processes such as photosynthesis, respiration, photosynthetic energy production and carbohydrate transport, and cell division and enlargement . Also, it is necessary for seed formation and is a fundamental element for nodule metabolism in legumes and is required to produce ATP, GTP, and CP as energetic substances and to regulate the activity of several proteins through phosphorylation reactions

Some ways to judge a crops health are to calculate its normalised difference vegetation index, NDVI; green normalised difference vegetation index GNDVI or LAI (Leaf area index).[7] Here we have implemented classification based on NDVI and GNDVI .

NDVI:

Various vegetation indices (e.g., normalised difference vegetation index, NDVI; green normalised difference vegetation index GNDVI; soil-adjusted vegetation index, SAVI) have been treated as indicators of vegetation biophysical variables (e.g., coverage, biomass and productivity).

NDVI and GNDVI mainly focus on the chlorophyll content in the leaves and accordingly provide values for the classified images. the NDVI and GNDVI classified images classify the original composite images of landsat in such way that it shows the entire image in a form of color spectrum. Its range various from -1 to 1 with -1 denoting the lower end and 1 denoting high NDVI value.

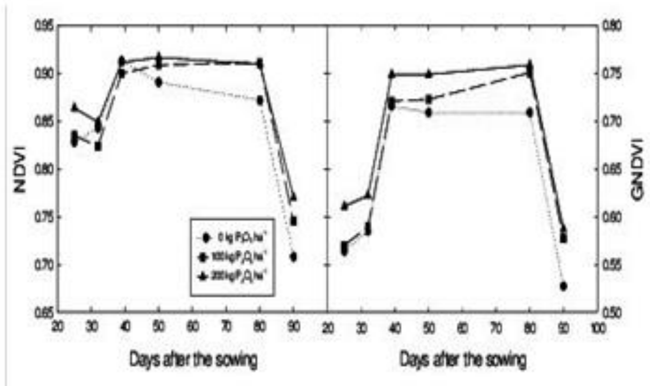

Fig II. Difference between NDVI and GNDVI [5]

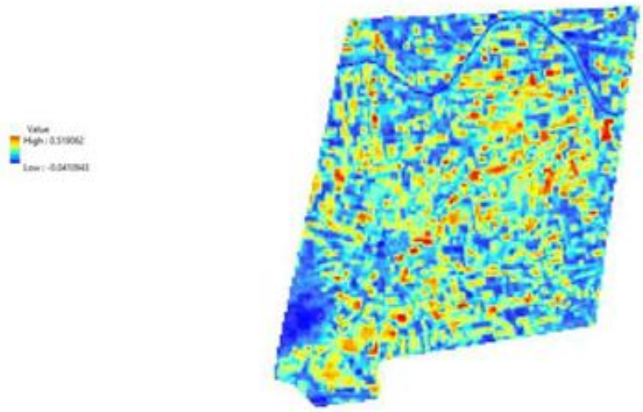

Fig III. NDVI image of Handigund village

Future Scope:

The implementation would be further taken forward with different bands over the same data and analysis for the same would be conducted and comparison between the data bands would be done for increasing the accuracy with the satellite data present.

The future implementation would include false colour composite images (FCC) which may increase the accuracy of the output using the same algorithm due to the presence of vegetation thermal band.

Conclusion:

In the study, detail analysis about different villages and study area was carried out and the approximate estimation of crops being present in the villages with estimation of pixels of a particular class was found. ML classifies pixels based on known properties of each cover type, but the generated classes may not be statistically separable. We also came to know that the band correlation of classes with high reflectance, e.g. sugarcane is high for all band pairs in ML because of the strong relationships of variation between the brightness of pixels.

Acknowledgement:

This project is supported by Godavari Biorefineries Limited(GBL) and carried out under the guidance of Mrs. Shyamal Virnodkar and Mrs Vricha Chavan , K J Somaiya Institute of Engineering and Information Technology, Mumbai University.

References:

[1]http://ieeexplore.ieee.org/document/6909319/?reload=tru

[2]http://web.pdx.edu/~jduh/courses/Archive/geog481w07/Students/Miller_HardSoftImageClassifications.pdf

[3]https://landsat.usgs.gov/landsat-8

[4]http://www.nrcan.gc.ca/node/9595

[5]https://www.researchgate.net/figure/NDVI-normalized-difference-vegetation-index-and-GNDVI-green-normalized-difference_fig2_228425763

[6]. Camelia Slave. 2014. Analysis of Agricultural Areas Using Satellite Images

[7]David B. Lobell and Gregory P. Asner. 2003. Comparison of Earth Observing-1 ALI and Landsat ETM+ for Crop Identification and Yield Prediction in Mexico

[8]N. Gökhan Kasapoglu, and Okan K. Ersoy. 2007. Border Vector Detection and Adaptation for Classification