

Classification of Crops from remotely sensed Images: An Overview

Rajesh K Dhumal*, YogeshRajendra,K.V.Kale,S.C.Mehrotra****

*Research Fellow,Research Fellow,**Professor& Head,
Department of Computer Science& IT, Dr.Babasaheb Ambedkar Marathwada University, Aurangabad (M.S.)
India.

**Professor, Srinivasa Ramanujan Geospatial Chair, Department of Computer Science & IT, Dr.Babasaheb
Ambedkar Marathwada University, Aurangabad (M.S.)India.

ABSTRACT

Crops identification from remotely sensed images is essential due to use of remote sensing images as an input for agricultural & economic planning by government & private agencies. Available satellite sensors like AWIFS, LISS (IRS series), SPOT 5 and also LANDSAT,MODIS are good sources of multispectral data with different spatial resolutions & Hyperion, Hy-Map, AVIRIS are good sources of hyper-spectral data. The methodology for this work is selection of satellite data; use of suitable method for classification and checking the accuracy.From last four decades various researchers have been working on these issues up to some extent but still some challenges are there like multiple crops identification, differentiation of crops of same type this paper provides an overall review of the work done in this important area. Multispectral & hyper-spectral images contain spectral information about the crops.Good soft computing & analysis skills are required to classify & identify the class of interest from that datasets.Various researchers have been worked with supervised & unsupervised classification along with hard classifiers as well as soft computing techniques like fuzzy C mean, support vector machine & they have been found different results with different datasets.

Keywords-*Crops Classification, Hypers-pectral, Multispectral,Microwave, Remote sensing, Microwave*

I. INTRODUCTION

Remote sensing, particularly satellites offer an immense source of data for studying spatial and temporal variability of the environmental parameters [1]. Remote sensing has shown great promise in identifying the crops grown in agricultural land. The resultant information has been found to be useful in the prediction of crop production and of land use. It plays a significant role for crop classification, crop health and yield assessment. Since the earliest stages of crop classification with digital remote sensing

data, numerous approaches based on supervised and unsupervised classification techniques have been used to map geographic distributions of crops with optical data and Characterize cropping practices. Hyper spectral data contains hypercube with no. of bands which also act as a good source of information. The smallest bandwidth of the hyper-spectral data tells fine detail about the crops along with internal contents.Microwaved remote sensing also gives some distinct information related to crops.

II. REMOTE SENSING FOR CROP CLASSIFICATION

Classification is the process where we convert multilayer input image in to single layer thematic map. However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification[2].Broadly there are two approaches for classification supervised and Unsupervised as shown in Fig.1. Unsupervised Classification is a clustering analysis in which pixel are grouped into certain categories in terms of the similarity in their spectral values. In this analytical procedure all pixels in the input Data are categorized into one of the groups specified by the analyst beforehand. Prior to the classification the image analyst does not have to know about scene or covers to be produced During post processing each spectral cluster get linked to meaningful Label related to actual ground cover. Supervised Classification is much more complex than Unsupervised classification.inwhich the Analyst should aware about ground cover. Process of supervised classification involves the selection of appropriate band with Definition ofsignature for training samples.These signature formsfoundation for the subsequent classification.Care must be taken in their selection. Selection of quality training samples requires knowledge of and understanding of the properties of the Different ground features in the satellite imagery.

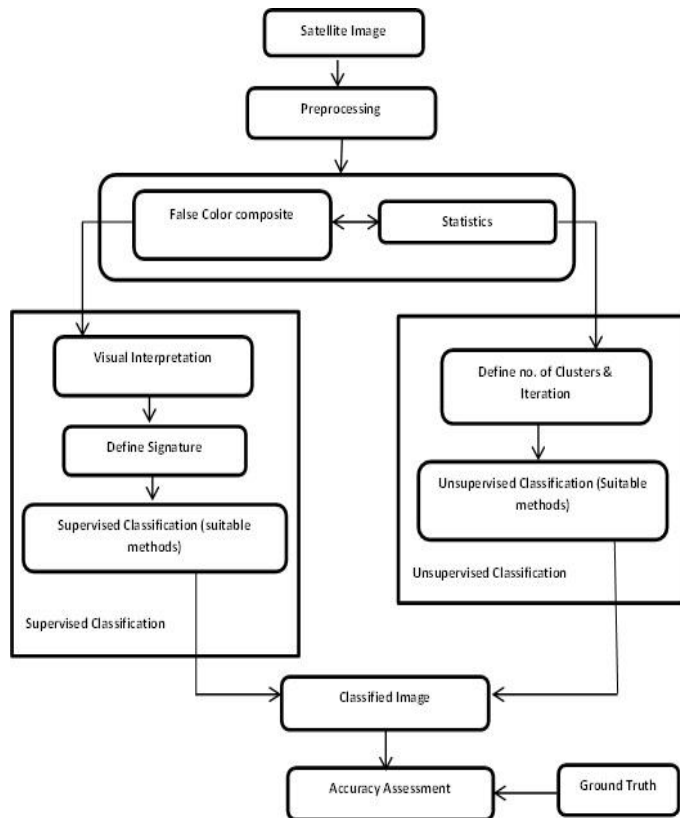


Figure 1. General methodology for classification of remotely sensed images (Supervised & Unsupervised approach).

Visual interpretation during classification is based on standard FCC (False Color Composite) generated using green, red and near-IR bands having assigned the display guns blue, green and red respectively. Each crop having their own distinct internal structures, some crops may have similarities, and due to distinctness of each crop they have different spectral signatures. It is complicated to classify crops with similar internal structure or similar reflectance behavior. In this case, hyper-spectral imagery plays important role to find the minute difference between these spectrally similar crops.

III. USE OF MULTISPECTRAL IMAGES

Multispectral remote sensing systems use parallel sensor arrays that detect radiation in a small number of broad wavelength bands. The multispectral airborne as well as satellite remote sensing technologies have been utilized as a widespread source for the purpose of remote classification of vegetation [3]. Depending on geographic area, crop diversity, field size, crop phenology and soil condition different band ratios of multispectral data and Classifications schemes have been applied [4] Nelis(1986) for example, used a maximum likelihood classification approach with Landsat data to map irrigated crop area in the U.S.

Further Preece in 1997 refined such approaches, using a multi-date Landsat Thematic Mapper (TM) dataset in southwest Kansas to map crop distribution and USDA Conservation Reserve Program (CRP) lands in an extensive irrigated area [4]. Multi temporal data improve the accuracy of classification SujayDatta et.al. have used LISS 1 Data for wheat crop classification by combining January & February two dates data & deriving their first two principle components they got 94 % classification accuracy[5]. K.R.Manjunath et.al(1998) have worked on IRS LISS II & LISS III for crops identification & concluded that spatial resolution & spectral band selection are affects on the classification results depending on crops area[6]. S.P.Vyaset.al. have used multi date IRS LISS III data for multi crop identification and crop area estimation in Utter Pradesh (India)[7]. They worked for mustard, potato & wheat crops after performing classification and comparing the result with single date classification results. They conclude that with the use of multi date IRS LISS III data it was possible to discriminate & map the various crops in the study area whereas single date is still good for homogeneous area & reduce data volume.

I. P. B. C. Leite^{atel}(2008) have worked on Hidden Markov Model (HMM) based technique to classify agricultural crops. They have used 12 Landsat images for 5 crop types, indicating a remarkable superiority of the HMM-based method over a mono temporal maximum likelihood classification approach. They got 94% accuracy and they conclude that HMM approach also performed well to recognize phenological stages of crops[8]. Qiong An *et al.*(2009) have used adaptive feature selection model In his work for rice crop with MODIS data the extracted spectral characteristics are analyzed using statistical method and dynamic changes of temporal series of indices including NDVI, EVI, MSAVI and NDWI are studied and by taking account of computational complexity & time effectiveness of calculation the Adaptive Feature selection model(AFSM) is studied. they got 94 % accuracy which was larger than general classification by 3%[9]. VijayaMusandeet. al. have worked for Cotton crop discrimination using fuzzy classifier approach in their work they have used temporal AWIFS & LISS III data sets of different months as per life cycle of cotton crops and by generating indices like NDVI, TNDVI, SAVI & TVI improved vegetation signals has been achieved [10].

IV. USE OF HYPER-SPECTRAL IMAGES

Hyper spectral remote sensing imagers acquire many, very narrow, contiguous spectral bands throughout the visible, near-infrared, mid-infrared, and thermal infrared portions of the electromagnetic spectrum as shown in Fig.2. Hyper spectral data contains huge volumes so it is difficult to classify crops from it with some traditional

classification techniques. The availability of hyper spectral data has overcome the constraints and limitations of low spectral and spatial resolution imagery, and discrete spectral signature. Prasad S. Thenkabai *et al.* (2002) have worked on Evaluation of Narrowband and Broadband Vegetation Indices for Determining Optimal Hyper spectral Wave bands for Agricultural Crop Characterization in their work they have used Landsat data with broad band narrow bands hyper spectral data with 430 bands in the visible & NIR portion of the spectrum.

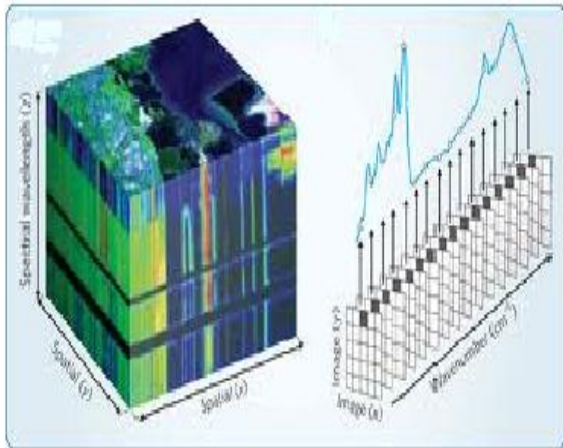


Figure 2. Conceptual Hyper spectral cube with continuous spectrum [18].

Study has been conducted for six crops namely barley, wheat, chickpea, lentil, vetch, and cumin by evaluating the various indices based on two bands. They have chosen only 12 bands out of 430 which provide optimal biophysical information about all 6 crops [11]. Some researcher proposed a procedure to reduce dimensionality of hyper spectral data while preserving relevant information for posterior crop cover classification through Local Correlation & Sequential Floating Forward Selection algorithm (HFFS) [12]. Xiangrong Zhang *et al.* (2009) have worked for a new feature extraction method based on immune clonal selection (ICSA) and PCA for classification of Hyper-spectral remote sensing image, they concluded that given method gives better classification results [13]. Farid Melgani and Lorenzo Bruzzone have used support vector machine for hyper-spectral image classification (2004) and they conclude that SVMs are more effective than Radial based function, neural networks and the K-nn classifier in terms of classification accuracy, computational time, and stability to parameter setting. SVMs seem to be more effective than other pattern recognition approaches based on the combination of a feature extraction/selection procedure and a conventional classifier, SVMs exhibit low sensitivity to the Hughes phenomenon, resulting in an excellent approach to avoid the usually time-consuming phase required by any feature-reduction method [14]. Shwetank *et al.* (2011) have used EO 1 Hyperion data

for rice crops classification they have developed the spectral library for rice crop and performed supervised classification with preprocessing & without preprocessing. Preprocessing involves radiometric correction, geometric correction and abnormal band and pixels Detection and correction. They used spectral angle mapper for classification & they got 86.96% accuracy for without preprocessed data and 89.33% accuracy for preprocessed data [15].

V. USE OF MICROWAVE REMOTE SENSING IMAGES

Microwave remote sensing, using microwave radiation with wavelengths from about 1 Centimeters to a few tens of centimeters enable observation in all type weather condition without any restriction by cloud or rain. That's why it can penetrate through cloud cover, haze, dust, and all but the heaviest rainfall. This is one of the advantages which is not possible with visible & infrared remote sensing. Microwave remote sensing provides unique information for sea wind and wave direction which are derived from frequency characteristics, Doppler's effect, Polarization, back scattering etc. That cannot be observed by visible and infrared sensors. Optical remote sensing is good source for crops classification in spite of that its limitation due to environmental interface like clouds which results into scattering effect & we can't get the fine details from that images. In that case Microwave Remote sensing plays good role. Operating in microwave region of the electromagnetic spectrum, improve signal penetration within vegetation & soil targets the longer wavelength of the RADAR system are not affected by cloud cover or haze. RADAR system transmits microwave signal at specific wavelength according to their design specification. Jesus Soria Ruiz *et al.* (2009) have worked on corn monitoring & crop yield using microwave & optical remote sensing & conclude that integration of SAR & optical data can improve the classification accuracy [16]. Jiali Shang *et al.* (2010) have worked on Multi-temporal RADARSAT-2 and TerraSAR-X SAR data for crop mapping in Canada & they found that When multi-frequency SAR (X- and C-band) are combined, classification accuracies above 85% are achieved prior to the end of season. Crops can be identified with accuracies between 86% (western Canada) and 91.4% (eastern Canada) [17].

VI. CONCLUSION

Remote sensing images act as good source for decision making related to crops monitoring & mapping in optical region. Multispectral images gives much detail for overall vegetation mapping in large area. Whereas it is having limitation due to broad wavelength & spatial resolution we can't differentiate crops of similar type. In that case

hyper-spectral images performs well, Selection of spectral bands in hyper-spectral images is also quite challenging task. By applying various hard as well as soft classifiers we can get good classification results. Some limitation of optical remote sensing can be overcome by fusing optical remote sensing images with microwave remote sensing images.

ACKNOWLEDGEMENTS

We are thankful to Department of Science & Technology for providing Srinavasa Ramanujan Geospatial Chair at Dr. Babasaheb Ambedkar Marathwada University Aurangabad (M.S) India.

REFERENCES

- [1] Perumal, K., and R. Bhaskaran. "Supervised classification performance of multispectral images." arXiv preprint arXiv:1002.4046 (2010).
- [2] Lu, D., and Q. Weng. "A survey of image classification methods and techniques for improving classification performance." *International Journal of Remote Sensing* 28.5 (2007): 823-870.
- [3] Landgrebe, David. "Information extraction principles and methods for multispectral and hyperspectral image data." *Information processing for remote sensing* 82 (1999): 3-38.
- [4] Nellis, M. Duane, Kevin P. Price, and Donald Rundquist. "Remote sensing of cropland agriculture." *The SAGE Handbook of Remote Sensing* 1 (2009): 368-380.
- [5] Dutta, Sujay, et al. "Wheat crop classification using multirate IRS LISS-I data." *Journal of the Indian Society of Remote Sensing* 26.1 (1998): 7-14.
- [6] Manjunath, K. R., N. Kundu, and S. Panigrahy. "Evaluation of spectral bands and spatial resolution of LISS II and LISS III sensors on-board IRS satellites for crop identification." *Journal of the Indian Society of Remote Sensing* 26.4 (1998): 197-208.
- [7] Vyas, S. P., M. P. Oza, and V. K. Dadhwal. "Multi-crop separability study of Rabi crops using multi-temporal satellite data." *Journal of the Indian Society of Remote Sensing* 33.1 (2005): 75-79.
- [8] Leite, P., et al. "Crop type recognition based on Hidden Markov Models of plant phenology." *Computer Graphics and Image Processing*, 2008. SIBGRAP'08. XXI Brazilian Symposium on. IEEE, 2008.
- [9] An, Qiong, et al. "Research on feature selection method oriented to crop identification using remote sensing image classification." *Fuzzy Systems and Knowledge Discovery, 2009. FSKD'09. Sixth International Conference on*. Vol. 5. IEEE, 2009.
- [10] Musande, Vijaya, Anil Kumar, and Karbhari Kale. "Cotton Crop Discrimination Using Fuzzy Classification Approach." *Journal of the Indian Society of Remote Sensing* (2012): 1-9.
- [11] Thenkabail, Prasad S., Ronald B. Smith, and Eddy De Pauw. "Evaluation of narrowband and broadband vegetation indices for determining optimal hyperspectral wavebands for agricultural crop characterization." *PE & RS-Photogrammetric Engineering & Remote Sensing* 68.6 (2002): 607-621.
- [12] Gomez-Chova, L., et al. "Feature selection of hyperspectral data through local correlation and SFFS for crop classification." *Geoscience and Remote Sensing Symposium, 2003. IGARSS'03. Proceedings. 2003 IEEE International. Vol. 1. IEEE, 2003.*
- [13] Xiangrong Zhang, Runxin Li and Licheng Jiao "Feature Extraction Combining PCA and Immune Clonal Selection for Hyperspectral Remote Sensing Image Classification", *International Conference on Artificial Intelligence and Computational Intelligence*, 2009.
- [14] Melgani, Farid, and Lorenzo Bruzzone. "Classification of hyperspectral remote sensing images with support vector machines." *Geoscience and Remote Sensing, IEEE Transactions on* 42.8 (2004): 1778-1790.
- [15] Shwetank, S., Kamal Jain, and Karamjit Bhatia. "Development of Digital Spectral Library and Supervised Classification of Rice Crop Varieties Using Hyperspectral Image Processing." *Asian Journal of Geoinformatics* 11.3 (2012).
- [16] Ruiz, Jesus Soria, Yolanda Fernandez Ordonez, and Heather McNairn. "Corn Monitoring and Crop Yield Using Optical and Microwave Remote Sensing."
- [17] Shang, Jiali, et al. "Contribution of TerraSAR-X Data to In-Season Crop Mapping in Canada." *Proceedings of TerraSAR-X Science Team Meeting*
- [18] http://www.nature.com/nphoton/journal/v3/n11/fig_tab/nphoton.2009.205_F3.html .(Image 2 source).
- [19] Gao, Jay. *Digital analysis of remotely sensed imagery*. McGraw-Hill Professional, 2008.
- [20] Shippert, Peg. "Introduction to hyperspectral image analysis." *Online Journal of Space Communication* 3 (2003).