HYPERSPECTRAL DATA ANALYSIS FOR MANGROVE SPECIES DISCRIMINATION: A NOVEL APPROACH

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ABSTRACT

Over the last 15 years, remote sensing has played a crucial role in mapping and understanding changes in the areal extent and spatial pattern of mangrove forests caused due to natural disasters and anthropogenic forces. While traditional pixel-based classification of multispectral imagery has been widely applied for mapping mangrove forests, more recent types of satellite imagery like hyperspectral data, taken from sensors like Hyperion combined with sub-pixel classification algorithms is expected to demonstrate the potential for reliable and detailed characterization of mangrove forests including species level classification. This paper brings forth the recent advancements in hyperspectral data and classification techniques and describes opportunities for integration of high spatial and spectral data for species level identification of mangroves. Future prospects include the application of existing methods in natural resource management and overcoming challenges in the global monitoring of mangrove forests.

Key words: Hyperspectral, Spectral Library, Ground Truthing, End Member Determination, Linear Spectral Unmixing, Non-linear Spectral Unmixing

I. INTRODUCTION

The ecological importance of mangroves is over exemplified in literature. They are a unique, yet undervalued and destroyed ecosystem, having had their initial global range reduced to less than 50% due to anthropogenic factors. For more than a decade, remote sensing has played a crucial role in mapping and understanding changes in the areal extent and spatial pattern of mangrove forests caused due to natural disasters and anthropogenic forces. While traditional pixel-based classification of Landsat, SPOT, LISS III, LISS IV and ASTER imagery has been widely applied for mapping mangrove forest, more recent types of satellite imagery, the hyperspectral data, taken from sensors like Hyperion combined with sub-pixel classification algorithms is expected to demonstrate the potential for reliable and detailed characterization of mangrove forests including species, leaf area, canopy height, and stand biomass. This paper is intended to move one step closer to the conclusion whether hyperspectral technology could be used for tropical mangrove species discrimination.

II. MULTISPECTRAL VS HYPERSPECTRAL

Multispectral sensors on satellite platforms, including synthetic aperture radar (SAR), Landsat TM, and SPOT XS are most popularly used for mangrove applications because of their cost-effective advantages(5), however they are mainly limited to the regional scale, owing to their relatively coarse spatial and spectral resolutions. Improvements are needed in both these major problem areas in order to enable mangroves to be studied at a finer level (4,5). Due to the lack of spectral details of multispectral sensors in which each band covers only a broad wavelength region of several tens of nanometers, the opportunities to exploit spectral responses linked to the physio-chemical properties of plants are lost.

In contrast, the report of Demuro and Chisholm (3) demonstrates how more delicate tools such as the satellite mounted HYPERION sensor (USGS EROS Data Center (EDC), USA) that possesses 242 bands between 400 nm and 2500 nm handles the task of discriminating eight-class mangrove communities (i.e. broad mangrove classes) in Australia, a task considered difficult for any multispectral sensor (5). Similarly, the 224-band Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor with an approximately 9.6-nm band width ranging between 400 nm and 2450 nm performs just as well in mapping the mangrove communities of the Everglades, Florida (9). Since both HYPERION and AVIRIS sensors collect a contiguous range of narrow-band spectral data, they are technically termed hyperspectral sensors.

The potential of hyperspectral technology has already been successfully established in the field of vegetation research (12, 9,13,16). This is because hyperspectral data contain information that relates to important biochemical properties of plants (8, 15, 11, 14). To highlight just a few, the recent applications of hyperspectral technology include the study of the quality of tropical pastures for animal grazing (13); the use of hyperspectral sensors to detect zinc stress in plants; and the extraction of crop biophysical parameters (6).

III. HYPERSPECTRAL DATA ANALYSIS AND CLASSIFICATION

Hyperspectral sensors typically measure brightness in hundreds of narrow, contiguous wavelength bands so that for each pixel in an image, a detailed spectral signature can be derived. A hyperspectral image can be viewed as a cube with spatial information represented in the X-Y plane. The third dimension, which is the Z-direction, is the spectral domain represented by hundreds of narrow, contiguous spectral bands corresponding to spectral reflectance.

Hyperspectral sensors oversample the spectrum signal in contiguous bands to ensure that features are well represented. This oversampling, and the wide frequency range of the energy reflected from the ground, result in hyperspectral data with a high degree of spectral redundancy. Identification of materials becomes more complex because a pixel, which is the lowest possible measured area, typically contains more than one material, which means it is a “mixed” pixel. The spectral signature of a mixed pixel is formed by the combination of the existing materials within the pixel. The analysis of hyperspectral imagery consists of several steps of processing the data as shown in Fig.1. for effective interpretation.

IV. METHODOLOGY

A. Acquisition of Hyperspectral Data

The hyperspectral data of the study area may be procured from Observatories through Data Acquisition Request (DAR).

B. Preprocessing of Data

The pre-processing stage can be considered as the first step to work with the data sets available and acquire the valuable information from the same. The data sets that are available to the user initially are in the raw form and most of the datasets are not geo-referenced to the ground. These datasets can also have errors due to atmospheric effects and need atmospheric corrections or radiometric calibrations. The users have data that contains lot of information and often user does not require the whole of it. Therefore spatial and spectral subsetting of the data is required which helps in reducing the complexities and the processing time on the image used. The various pre-processing steps which may be carried out are as follows:

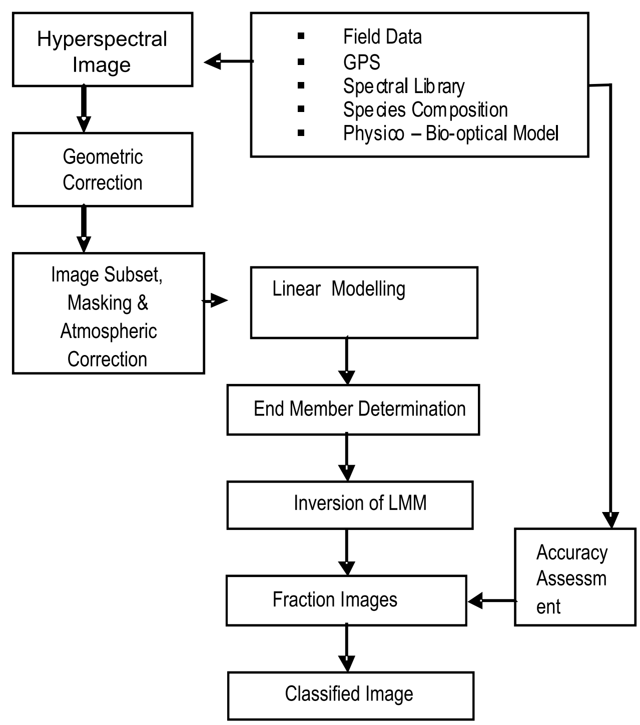

Fig. 1. Schematic Layout of Major Activity Components

Atmospheric Correction of the Hyperion data

Sophisticated atmospheric correction algorithms have been developed to calculate concentrations of atmospheric gases directly from the detailed spectral information contained in hyperspectral imagery, without additional data about atmospheric conditions.

The steps in the pre-processing of Hyperion for the radiometric correction of the Level 1R include Short Wave Infrared (SWIR) smearing, removal of the bands having no information, removal of the line dropouts, removal of the line striping in the various bands, and removal of the absorption bands. The SWIR and the VNIR (visible near-infrared) bands are scaled; subsets of the bands are specified; abnormal pixels are corrected and finally geometric correction is done.

Geo-referencing of the Hyperion data

Geometric correction is undertaken to avoid geometric distortions from a distorted image and is achieved by establishing the relationship between the image co-ordinate system and the geographic coordinate system using calibration data of the sensor, measured data of position and attitude, the ground control points, atmospheric conditions, etc.

Dimensionality Reduction

Although hyperspectral imagery provides a repository of information about a scene, a serious drawback of such increased spectral resolution is the large size of the dataset generated for each image. The large datasets are difficult to manage, impede data transmission and make data mining difficult. To overcome this high dimensionality of the data, Principal Component Transformation (PCT)/Principal Component Analysis (PCA) and Maximum Noise Fraction (MNF) may be applied to reduce the number of bands in order to allow for better outcomes and faster processing.

Integration and Mixing of Hyperspectral and Higher Spatial Resolution Data

The fusion of hyperspectral with multispectral image results in a new image which has the spatial resolution of the high resolution image and all the spectral characteristics of the hyperspectral image. Hyperspectral data fusion is the latest approach to acquire significant and reliable information that can't be acquired with fusion of multispectral and panchromatic images. There are various image fusion approaches that are widely used to obtain the information. There are some algorithms used specifically to fuse and classify the hyperspectral data with the multispectral data. Some of the algorithms are transformation based (e.g. Intensity, Hue, Saturation), wavelet decomposition, neural networks, knowledge-based image fusion, Colour Normalised Transform (CNT), Principal Component Transform (PCT) and the Gram-Schmidt Transform. (1).

C. Ground Survey for Creation of Spectral Library

One important and major component of species identification is the creation of spectral library which may be developed specifically for the mangrove species of the study area. Portable multi-channel spectro-radiometer that operates within a desired hyperspectral range and spectral resolution may be used to build a spectral library of these mangrove species.

The spectral reflectance of all the species measured in the field may be further re-sampled to suit the spectral bands of the hyperspectral imagery. A ground survey of the study area (as far as accessible and practically possible) should be made to identify and collect samples of the species whose image based classification is proposed to be carried out.

As already stated in an earlier section, the creation of spectral library is possible because of the fact that the important biophysical and biochemical properties of plants lead to significant bio-optical sensitivity that are rightly reflected in the pattern of curves that are generated by the spectro-radiometers. Proper scrutiny and detailed examination of the frequency, intensity and position of kinks (peaks and valleys) in these spectral curves can only lead to a rational and exact identification and discrimination of species in a mixed forest stand. Hence creation of the spectral library for the species mix of the study area is of paramount importance in the classification process.

D. Stratification

Sub-setting and masking of water bodies and clouds may be done to ensure exact delineation of the mangrove canopy from the non-mangrove entities which would then be filtered out for further processing.

E. Image Classification Technique : Spectral Mixture Analysis

The image classification may be done with the help of existing image processing software packages, such as ENVI, MATLAB, ERDAS, as found suitable for developing and executing the algorithms related to the present study problem.

The spectral mixture analysis may be done with the help of a model developed on an algorithm. The model will bring out how a given pixel mixed with a variety of components provide the procedure in unmixing of pixels. Linear mixing model, which is a commonly used procedure in bringing about linear spectral unmixing, will be applied here.

Linear Spectral Unmixing

This method has gained considerable significance in solving the mixed-pixel problem and generates fraction images of each ground cover class. The linear spectral unmixing classification is based on a two-step approach:

End Member Determination: This is done to estimate the set of distinct spectra (end members) that constitute the mixed pixels in the imagery. Spectrally unique signatures of pure ground components, usually known as end members, are determined.

Inversion: Inversion is done to estimate the fractional abundances of each mixed pixel from its spectrum and the end member spectra. It is done by inverting the linear mixing equation through least square regression technique.

The best results are obtained when:

(a) the fraction values for each end-members fall between 0.0 to 1.0

(b) the sum of all end-members fraction is equal or less than one for a pixel

(c) the RMS error is between 0.00-0.05.

F. Accuracy Assessment

Lastly, the accuracy assessment may be performed using :

(i) random sampling and checks to find out the level of accuracy between the image derived and field measured fraction values

(ii) Kappa coefficient to achieve overall sampling accuracy which will take care of the overall mapping accuracy and

(iii) area based confusion matrix.

V. CONCLUSION

The uniqueness of the present paper lies in the fact that hyperspectral image classification algorithm has rarely been developed for mangrove classification across the world. This study is essentially poised to redress some of the unsolved issues so far faced by researchers in species level classification of mangroves. The spectral library and algorithm that may be developed on the basis of the bio-optical properties of the studied mangrove species is a unique advantage of hyper-spectral data that provides room to exploit the finer relationships between the mangroves and their spectral characteristics. The same will be integrated with the classification procedure in order to enhance the quality of the final output (mangrove species delineation map). The methodology presented in this study can be used as guidelines for producing a mangrove map at a detailed level (species level). The fraction images of species derived from the Linear Mixture Modelling (LMM) of remotely sensed data can be utilized for mangrove resource management. The result of this classification process is also expected to provide interesting clues in making further investigation into the capabilities of on-board hyper-spectral sensors for mangrove species discrimination.

VI. FUTURE PROSPECTS

In future, the developed algorithm using hyperspectral imagery can be further improvised and suitably tailor-made for use in natural resources monitoring/management like agriculture (crop condition assessment and crop acreage yield estimation), forest coverage and deforestation, urban infrastructure development, land use and wasteland mapping, coastal features mapping, coral reef mapping and land slide studies.

An attempt may be made to develop an algorithm for non-linear spectral unmixing (that will lead to non-linear mixing model) which will probably be the first unique attempt for mangrove classification. This is expected to produce more accurate classification results as compared to the linear spectral unmixing classifier. The non-linear mixing technique can also be applied to other fields of research, such as to identify and study the heterogeneous mix of Indian cropping system, of poly-metallic mineral outcrops in virgin non-covered areas, study of tropical pastures for animal grazing, extraction of crop biophysical and biochemical parameters in biogeochemical surveys, etc. Hence there is tremendous scope of replicability of the research outcome.

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REFERENCES

[1] Ali Darvishi, B., Kuppas, M. and Erasmi, S., 2005. Hyper-spectral/High resolution Data fusion:Assessing the quality of EO1 - Hyperion/spot-Pan and Quickbird-MS fused Images in spectral Domain.

[2] Boardman J.W. 1989 Inversion of imaging spectrometry data using singular value decomposition. *Proceedings,* IGARSS '89, 12th Canadian Symposium on Remote Sensing.4, 2069-2072.

[3] Demuro, M., Chisholm, L., 2003. Assessment of Hyperion for characterizing mangrove communities. In: Proceedings of the International Conference the AVIRIS 2003 Workshop, pp. 18-23.

[4] Gao, J., 1999. A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. International Journal of Remote Sensing 20, 2823-2833.

[5] Green, R.O., Eastwood, M.L., Sarture, C.M., Chrien, T.G., Aronsson, M., Chippendale, B.J., Faust, J.A., Pavri, B.E., Chovit, C.J., Solis, M., Olah, M.R., Williams, O., 1998. Imaging spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). Remote Sensing of Environment 65,227e248.

[6] Goel, P.K., Prasher, S.O., Landry, J.A., Patel, R.M., Viau, A.A., Miller, J.R., 2003. Estimation of crop biophysical parameters through airborne and field hyperspectral remote Sensing. Transactions of the American Society of Agricultural Engineers 46, 1235e1246.

[7] Gates, D.M., Keegan, H.J., Schleter, J.C., Weidner, V.R., 1965. Spectral properties of plants. Applied Optics 9, 545e552.

[8] Hoffer, R.M., 1978. Biological and physical considerations in applying computer aided analysis techniques to the remote sensor data. In: Swain, P.H., Davis, S.M. (Eds.), Remote Sensing: The Quantitative Approach. McGraw-Hill, New York, pp. 227e289.

[9] Hirano, A., Madden, M., Welch, R., 2003. Hyperspectral image data for mapping wetland vegetation. Wetlands 23, 436e448.

[10] Held, A., Ticehurst, C., Lymburner, L., Williams, N., 2003. High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. International Journal of Remote Sensing 24, 2739-2759.

[11] Kokaly, R.F., 2001. Investigating a physical basis for spectroscopic estimates of leaf nitrogen concentration. Remote Sensing of Environment 75, 267e287

[12] Kruse, F.A., Boardman, J.W., Lefkoff, A.B., Young, J.M., Kierein-Young, K.S., Cocks, T.D., Jenssen, R., Cocks, P.A., 2000. HyMap: an Australian hyperspectral sensor solving global problems eresults from USA HyMap data acquisitions. In: Proceeding of the International Conference Australasian Remote Sensing and Photogrammetry, pp. 18e23.

[13] Mutanga, O., Skidmore, A.K., Van Wieren, S., 2003. Discriminating tropical grass (Cenchrus ciliaris) canopies grown under different nitrogen treatments using spectroradiometry. ISPRS Journal of Photogrammetry and Remote Sensing 57, 263e272.

[14] McDonald, M.S., 2003. Photobiology of Higher Plants. Wiley,Chichester, 354 pp.

[15] Peterson, D.L., Hubbard, G.S., 1992. Scientific issues and potential remote sensing requirements for plant biochemical content. Journal of Image Science and Technology 36, 446e456.

[16] Zarco-Tejada, P.J., Miller, J.R., Morales, A., Berjo n, A., Agu era, J., 2004. Hyperspectral indices and model simulation for chlorophyll estimation in open-canopy tree crops. Remote Sensing of Environment 90, 463e476.

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