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Advances in Classification of Crops using Remote Sensing Data

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Abstract Remote sensing is an efficient technology and worthy source of earth surface information, as it can capture images of reasonably large area on the earth. Due to advancement in the sensor technologies there is availability of high spatial as well as spectral resolutions imageries, and also non imaging Spectroradiometer. With the use of these imaging and non-imaging data we can easily characterize the different species. In this article we have reported work done by worldwide researchers for spatial as well as spectral feature extraction from remote sensing data; specifically we have focused on classification of crops and use narrow band vegetation indices. It may be observed from the report that both spatial resolution and hyperspectral imageries need to be used for better classification.
Keywords *Spatial Features; Spectral Features; Hyperspectral Data; Crops Classification*

1. Introduction

Crops are very distinct in their development stages. In general, the major crops in India can be divided into four categories as Food grains like Rice, Wheat, Maize etc, Cash Crops like Cotton, Sugarcane, etc. Plantation Crops like Tea, Coffee, Coconut and Horticulture crops such as Fruits and Vegetables; also cultivated crops can be classified into three main groups according to the duration of the life cycle, yearly, perennial, and semiperennial crops. Yearly crops are planted once or even two-three times a year. A perennial crop can stay in field for many years, while a semiperennial crop remains in field only for a few years. The duration of the crop cycle impacts on the chances of acquiring cloud-free images using optical remote sensing, which are obviously higher for perennial crops. Especially for yearly crops, due to their short life cycle, another important aspect for remote sensing is how they are split into development stages. Different crops show distinct phonological characteristics and timings according to their nature germination, tillering, flowering, ball formation (e.g., cotton), ripening, and so forth. Even for the same crop and growing season, the duration and magnitude of each phonological stage can differ between the varieties, which introduce data variability for crop type discrimination with imaging systems (Galvao, L.S., 2011). Agricultural crops are significantly better characterized, classified, modeled and mapped using hyperspectral data. There are many studies supporting this, conducted on a wide array of crops and their biophysical and biochemical variables (Prasad, S.; Thenkabail et al., 2011). The importance of analyzing both spectral and spatial patterns has been identified as a desired goal by many scientists devoted to multidimensional data analysis. This type of processing has been approached from various points of view representing different levels of combination between spectral and spatial information (Victor Alchanatis and Yafit Cohen, 2011).

2. Feature Extraction

Feature Extraction is the process of defining Image characteristics or features which effectively provides meaningful information for image interpretation or classification. The ultimate goals of feature extraction are

1) Effectiveness and efficiency in classification;
2) To avoid redundancy of data;
3) To smartly identify useful spatial as well as spectral features;
4) To maximize the pattern discrimination.

3. Spatial Features

For crop type discrimination spatial features are useful. As crops are planted in rows or straight lines either multiple or single rows as per the crop types for convenience and to enhance maximum yields. The different spatial arrangement of the crops gives better spatial information but it requires high spatial resolution images. In spatial image classification, spatial image elements are combined with spectral properties in reaching a classification decision. Most commonly used elements are texture; contexture and geometry i.e. shape (Jay Gao, 2009). Due to the availability of commercial high resolution multispectral satellite imagery such as Geoeye-1, IKONOS-2, QuickBird -2 with less than 4 m spatial resolution it has become possible to identify small-scale Features from complex environments. However, there have been limitations when using only the spectral information because of the complex spatial arrangement of features and the spectral heterogeneity within each class (Han, Youkyung, et al., 2012).

3.1. Role of Texture in Classification

In general, it is possible to distinguish between the regular textures manifested by man-made objects from the irregular manner that natural objects exhibit texture. Hence, the texture characteristic can be used to discriminate between divergent objects. Therefore, they support their segmentation from remotely sensed data, both the conventional texture analysis and the grey level co-occurrence matrix (GLCM) methods describing the grey value relationships in the neighborhood of the current pixel. However, in the GLCM method, this is analyzed within the GLCM space and not from the original grey values, as is the case in the former method (Kiema, J. B. K., 2002).

3.2. Gray Level Co-occurrence Matrix (GLCM)

GLCM can be viewed as a two-dimensional histogram of the frequency with which pairs of grey level pixels occur in a given spatial relationship, defined by a specific c inter-pixel distance and a given pixel orientation. Hence, in the segmentation of urban objects, texture analysis is usually performed within a GLCM matrix space (Kiema, J.B.K., 2002). A variety of texture measures can be extracted from the GLCM. Four useful measures that can be derived from the probability density P_δ(i,j) are energy, variance, dissimilarity and homogeneity where energy p (I,j) measures the uniformity of the texture, variance measures, the heterogeneity of the pixel values. Similar to contrast dissimilarity measures the difference between adjoining pixels and homogeneity measures the tonal uniformity (Jay Gao, 2009).

In this regard Li, Z. et al. has worked on spectral and texture features for object-based vegetation classification at the species level using airborne high resolution multispectral imagery. Image-objects as the basic classification unit were generated through image segmentation. Statistical moments extracted from original spectral bands and vegetation index image are used as feature descriptors for image objects (i.e. tree crowns). They have also used several state-of-art texture descriptors such as Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Patterns (LBP) and its extensions are extracted for comparison purpose. Support Vector Machine (SVM) is used for classification in the object-feature space. The experimental results showed that incorporating spectral vegetation indices can improve the classification accuracy and obtained better results than in original spectral bands, and using moments of Ratio Vegetation Index obtained the highest average classification accuracy in this experiment. The experiments also indicate that the spectral moment features also outperform or can at least compare with the state-of-art texture descriptors in terms of classification accuracy (Li, Zhengrong, et al., 2010)

3.3. Local Binary Pattern (LBP)

It is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational plainness, LBP texture operator has become a popular approach in various applications. It can be seen as a uniting approach to the traditionally divergent statistical and structural models of texture analysis. Possibly the most important assets of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes instigated, for example, by illumination differences. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings (Ojala et al., 2002; Matti Pietikäinen, 2010). Spatial feature extraction for crop type discrimination works well if we have high spatial resolution satellite imagery. Rather than this, spatial information is also useful in spectral based classification for visual interpretation in supervised learning.

4. Spectral Features for Crop Classification

Spectral characteristics of green vegetation have very noticeable features two valleys in the visible portion of the spectrum are determined by the pigments contained in the plant. Chlorophyll absorbs strongly in the blue (0.4-0.5um) and red (0.68 um) regions, also known as the chlorophyll absorption bands. Chlorophyll is the primary photosynthetic pigment in green plants. This is the reason for the human eye perceiving healthy vegetation as green. When the plant is subjected to stress that hinders normal growth and chlorophyll production, there is less absorption in the red and blue regions and the amount of reflection in the red waveband increases.

The spectral reflectance signature has a dramatic increase in the reflection for healthy vegetation at around 0.7 um. In the near infrared (NIR) between 0.7 um and 1.3 um, a plant leaf will naturally reflect between 40% and 60%, the rest is transmitted, with only about 5% being adsorbed. For comparison, the reflectance in the green range reaches 15%–20%. This high reflectance in the NIR is due to scattering of the light in the intercellular volume of the leaves mesophyll. Structural variability in leaves in this range allows one to differentiate between species, even though they might look the same in the visible region. Beyond 1.3 um, the incident energy upon the vegetation is largely absorbed or reflected with very little transmittance of energy. Three strong water absorption bands are noted at around 1.4, 1.9, and 2.7 um and can be used for plant water content estimation (Victor Alchanatis and Yafit Cohen, 2011). Reflectance behavior of vegetation is given in Figure 1 (Muhammad Aqeel Ashraf et al., 2011). The spectral signatures of crop canopies in the field are more complex and often quite dissimilar from those of single green leaves measured under carefully controlled illumination conditions. Even when leaf spectral properties remain quite constant throughout the season, canopy spectra change vigorously as the proportions of soil and vegetation change and the architectural arrangement of plant components vary (Pinter Jr, Paul J., et al., 2003). Following steps (4.1 and 4.2) will improve the feature extraction process from hyperspectral data.

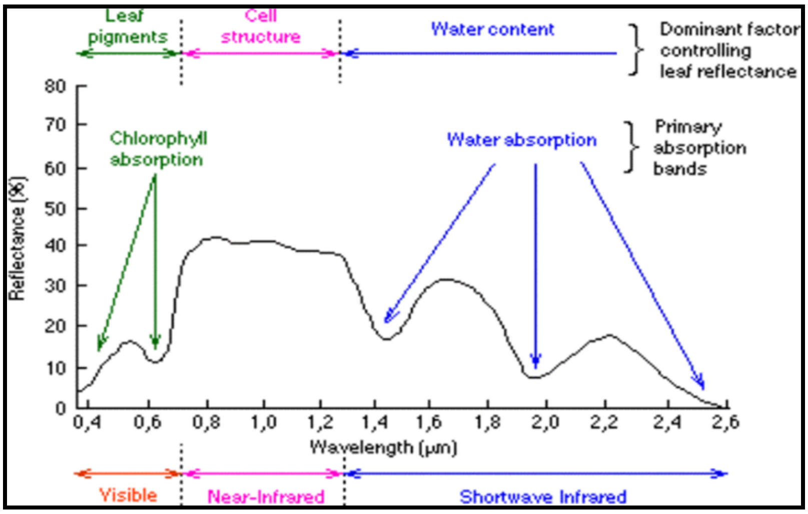

Figure 1: *Reflectance Behavior of Vegetation*

4.1. Band Selection

Band selection is one of the important steps in hyperspectral remote sensing, there are two conceptually different approaches of band selection can be used like unsupervised and supervised. Due to because of availability of hundreds of spectral bands there may be same values in several bands which increase the data redundancy. To avoid the data redundancy and to get distinct features from available hundreds of bands we have to choose the specific bands, so by studying the reflectance behavior of crops we can select distinct information bands (Roberts, Dar A., et al., 2011).

4.2. Narrowband Vegetation Indices

Spectral indices assume that the combined interaction between a small numbers of wavelengths is adequate to describe the biochemical or biophysical interaction between light and matter. The simplest form of index is a simple ratio (SR), a potentially greater contribution of hyperspectral systems is their ability to create new indices that integrate wavelengths not sampled by any broadband system and to quantify absorptions that are specific to important biochemical and biophysical quantities of vegetation. Examples include most of the pigment-oriented indices, all indices formulated for the red edge, several water absorption indices, and indices that use three or more wavelengths. Vegetation properties measured with Hyperspectral Vegetation indices (HVIs) can be divided into three main categories: (1) structure; (2) biochemistry; and (3) plant physiology/stress (Roberts, Dar A. et al., 2011).

4.2.1 Structural Properties

These properties include fractional cover, green leaf biomass, leaf area index (LAI), senesced biomass, and fraction absorbed photosynthetically active radiation (FPAR). A majority of the indices developed for structural analysis were formulated for broadband systems and have narrowband, hyperspectral equivalents.

4.2.2. Biochemical Properties

It include water, pigments (chlorophyll, carotenoids, anthocyanins), other nitrogen-rich compounds (e.g., proteins), and plant structural materials (lignin and cellulose).

4.2.3. Physiological and Stress Indices

It measure subtle changes due to a stress-induced change in the state of xanthophyll's, changes in chlorophyll content, fluorescence, or changes in leaf moisture. In general, biochemical and physiological/stress indices were formulated using laboratory or field instruments (≤10 nm spectral sampling) and are targeted at very fine spectral features (Roberts, Dar et al., 2011).

Narrowband vegetation indices can be used as potential variables for crop type discrimination. Lenio Soares Galvao et al. in their article has suggested the several best vegetation indices of different category to discriminate the seven crop types which are greenness/leaf pigment indices (ARVI, EVI, NDVI, and SGI); chlorophyll red edge indices (RENDVI and VOG-1); light use efficiency indices (SIPI and PRI); and leaf water indices (DWSI and NDWI) (Galvao, 2011) Given in Table 1.

Table 1: *Narrowband Vegetation Indices*

Sr. No.	Index	Acronym	Formula*	Reference
1	Normalized difference vegetation index	NDVI	(ρ864 − ρ671)/(ρ864 + ρ671)	Rouse et al.
2	Simple Ratio	SR	ρ864/ρ671	Rouse et al.
3	Enhanced Vegetation Index	EVI	2.5([ρ864 − ρ671]/[ρ864 + 6 × ρ671 − 7.5 × ρ467 + 1])	Huete et al.
4	Atmospherically Resistant Vegetation Index	ARVI	(ρ864 − [2 × ρ671 − ρ467])/(ρ864 + [2 × ρ671 − ρ467])	Kaufman et al.
5	Sum Green Index	SGI	(ρ508 + ρ518 + ρ528 + ρ538 + ρ549 + ρ559 + ρ569 + ρ579 + ρ590 + ρ600)/10	Lobell and Asner.
6	Red Edge Normalized Difference Vegetation Index	RENDVI	(ρ752 − ρ701)/(ρ752 + ρ701)	Gitelson et al.
7	Vogelmann Red Edge Index	VOG-I	ρ742/ρ722	Vogelmann et al.
8	Structure Insensitive Pigment Index	SIPI	(ρ803 − ρ467)/(ρ803 + ρ681)	Penuelas et al.
9	Photochemical Reflectance Index	PRI	(ρ529 − ρ569)/(ρ529 + ρ569)	Gamon et al.
10	Disease Water Stress Index	DWSI	ρ803/ρ1598	Apan et al.
11	Normalized Difference Water Index	NDWI	(ρ854 − ρ1245)/(ρ854 + ρ1245)	Gao et al.

*ρ is the reflectance of the closest Hyperion bands (*n,* center in nanometers) to the original wavelength formulations.

5. Importance of Hyperspectral Remote Sensing Data

Now a days hyperspectral remote sensing has stepped into a new stage in all over the world. There are several advanced hyperspectral imaging systems developed has been playing a very important role for agricultural application. Thenkabail et al. in their paper has pointed out that, Hyperion imaging spectrometer onboard the Earth Observing One (EO-1) satellite has provided significantly enhanced data, over conventional multi-spectral remote sensing systems. Hyperspectral narrowband (HNBs) and hyperspectral vegetation indices (HVIs) derived from EO-1 and field spectral measurements in the 400–2500 nm spectrum allow us to study very specific characteristics of agricultural crops (Thenkabail Prasad et al., 2013). Non imaging sensors as discussed earlier also give fine spectral signatures with approximate 1-10 nm sampling rate, which is very effective for distinct feature identification. Sayed M. Arafat et al. has used field hyperspectral remotely sensed data in their experiment. They applied One Way ANOVA and Tukey's HSD post hoc analysis to choose the optimal spectral zone that could be used to differentiate the different crops. Linear regression discrimination (LDA) was applied to identify the specific optimal wavebands in the spectral zones in which each crop could be spectrally identified (Arafat Sayed et al., 2013). The availability of hyper spectral data overcomes the constraints and limitations of low spectral resolution i.e. Multispectral imagery (Dhumal Rajesh K. et al., 2013).

Victor Alchanatis and Yafit Cohen have mentioned the importance of hyperspectral images in terms of their unique spectral bands, spatial attributes and image processing algorithms that show the added value of spatial information when combined with spectral information for mapping plant biophysical and biochemical properties of agricultural crops (BB-PACs) (Victor Alchanatis and Yafit Cohen, 2011). After considering the limitation and advantages of Hyperspectral and multispectral data we have attempted to find combined approach for the problem. The Table 2 given bellow shows how researchers have followed multidimensional approach for different applications.

***Table 2**: Use of Spatial and Spectral Approach with Different Datasets*

Sr. No.	Author and Year of Publication	Datasets	Approach		Results
			Spectral	Spatial	
1	Prasad S. Thenkabail et.al,(2013)	Hyperion EO and Field reflectance data	Identified Optimal hyperspectral narrowbands (HNBs) and hyperspectral vegetation indices (HVIs) were identified for the study of eight major agricultural worldwide crops	--	Got 95 % of overall accuracy.
2	Z. Li et.al,(2010)	Airborne high resolution multispectral imagery	Ratio Vegetation Index, Support vector machine	Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Patterns (LBP)	Vegetation indices improves the classification accuracy than spectral band
3	Antonio Plaza el.al ,(2002)	Multispectral-Hyperspectral (AVIRIS)	Unsupervised classification and spectral information for morphological operation	Mathematical morphological operations	The proposed method is accurate in the task of identifying end members from complicated scene
4	Gustavo Camps-Valls,(2010)	Hyperspectral AVIRIS data	Graph kernel for spatio-spectral remote sensing image classification with support vector machines		The proposed kernel is a powerful alternative to existing approaches
5	Shwetank1 et.al (2011)	EO-1 Hyperion data For crop classification	Spectral Angle Mapper		Development of spectral library and the SAM algorithm gives 89.33% overall accuracy and map the rice based agricultural area better than before Pre-processing Classification 86.96%.
6	Liangpei Zhang et.al,(2006)	HSRS Quick bird and IKONOS with multispectral band	PCA, ICA spectral transform.	PSI, Shape features	Use of PSI in conjunction with PCA or ICA and SVM improves the classification accuracy
7	A.N. Tassetti et al.,(2010)	IKONOS multispectral Images	NDVI feature and TDVI masks	GLCM and edge-density features	achieved an accuracy of 80.01% compared to 63.44% of accuracy achieved by using the few spectral bands only
8	C. S. Murthy et al., (2010)	IRS-1B LISS II for Wheat crop classification	s_MLC, pca_MLC, i_MLC, Artificial Neural Networks (ANN) with back-	--	i_MLC has resulted in relatively better classification of wheat whereas ANN

			propagation method		classification is superior to that of i_MLC
9	Sayed M. Arafat,(2013)	Spectral Data from Fieldspec3 for 4 crops discrimination	ANOVA and Tukey's HSD post hoc analysis and Linear Discriminant Analysis.	--	They have identified optimal spectral range to discriminate the crops

6. Conclusion

Both spatial and spectral information are necessary for better discriminations of species. Hyperspectral data gives detail information about crops but it is necessary to select appropriate bands, Narrowband vegetation indices plays important role for mapping plant biophysical and biochemical properties of agricultural crops (BB-PACs). Combination of spatial and spectral feature can be used effectively to discriminate the crops types but available hyperspectral imageries have not provided good spatial resolution which doesn't give proper spatial information. So that, we need to include both, good spatial resolution and hyperspectral imageries for better information extraction.

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