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Advances in Land Use classification of Urban Areas from Hyperspectral Data

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Abstract:

Land Use Land Cover (LULC) of urban environments covers natural and manmade resource. Because of this mix structured, the spatial and spectral characteristics of a targets and backgrounds are extremely diverse. Due to this problem, detection and the classification of manmade objects is very difficult. A Hyperspectral Remote Sensing can allow us to perform a detailed analysis of the urban area; it uses advanced imaging or non-imaging instruments to produce data with hundreds of spectral bands. These data are more useful for urban region, and by using this we can identify more objects and can generate more classes.

Keywords — **Hyperspectral Remote Sensing; EO-1 Hyperion; LULC; Spectral Angle Mapper; PCA.**

I. INTRODUCTION

The rapid growth in urbanization is creating huge demand in a very short-span of time for infrastructure and other services which is simply beyond the capacity of the local governance. In Urban planning a Land Use Land Cover (LULC) analysis by using Remote Sensing and GIS is a very important to make better decisions. A GIS can be used to monitor LULC, Urban Growth, and Change Detection etc. [1] [2]. RS and GIS support a wide range of planning and management operations that make an enormous impact towards guiding the development and growth of urban areas [3]. Rather than finding optimal solutions, pragmatically approaches must depend on the usage of heuristic problems capable of supporting the dynamic requirements of the domain [4]. When a non-spatial attributes is associated with the spatial entity, so it will be more useful to achieve most consecutive infrastructure strategy. This is a key factor for applying RS and GIS technology as a tool for identification of LULC [5] [6] [7].

Population growth and urban expansion have sublimate at a remarkably pace over the past several decades. Even though cities occupy only a small portion of the Earth's total land surface, almost half of the world's population lives in urban area. Urban growth has had increasingly significant socioeconomic and environmental impacts at local, regional and global scales [8]. Due to the rapid expansion and development of urban centers and cities, new methods are needed for the frequent updating of existing databases instead of standard methods, which are mostly based on field investigations and the visual interpretation of Remote Sensing Images [9] [10] [11]. In Urban development the traditional methods are time-consuming and expensive. Developments in remote sensing technology during the last several years provide an innovative set of airborne and space borne systems with improved spectral and spatial mapping capabilities [3].

Remotely-sensed data and imagery provide a comprehensive, scalable means for detecting and quantifying land use land cover change, and its use in mapping urban growth, estimating population density, and modeling sustainability and quality of life is becoming increasingly popular as the scale, cost, and spatial-temporal coverage improves. An airborne and satellite Remote Sensing's Multispectral images has been used as a source data for water and land observational applications since the 1960s. Advances in sensor technology have made it possible for the collection of several hundred spectral bands. This is commonly referred to as Hyperspectral imagery. An airborne and satellite Multispectral system have been used for collecting data in the fields of agriculture, food production, geology, geography and urban to non-urban localities, oil and mineral exploration. In Multispectral remote sensing to detect a radiation in a small number of broad wavelength bands it uses parallel sensor arrays [8] [12]. A Remote Sensing Systems which acquires multiple and very narrow, contiguous spectral bands from visible, near-infrared, mid-infrared, and thermal infrared portions of the electromagnetic spectrum is called as Hyperspectral Remote Sensing; these sensors normally collects 200 or more bands [9]. In Hyperspectral imaging systems it required a new processing System, because it combines imaging and spectroscopy in a single system that often includes large datasets. Hyperspectral datasets are generally composed of approximately 100 to 200 or more spectral bands with relatively narrow bandwidths (5-10 nm), whereas multispectral datasets are usually composed of approximately 5 to 10, relatively wider bands [13].

II. LITERATURE REVIEW

Hyperspectral images are captured by the spectral sensors which are sensitive to larger portion of the electromagnetic spectrum than the traditional color cameras. The idea behind the remote sensing technology relies on the relationship between photons and surface materials. While a digital color camera can capture only 3 bands (Red, Green, and Blue) in the range of 400 nm to 700 nm spectral wavelength, a typical Hyperspectral sensor captures more than 200 bands within the range of 400 nm to 2500 nm. This means that Hyperspectral imagery offers 200 or more features for an image pixel, instead of 3 values. Hyperspectral imagery contains diverse information from a wide range of wavelengths. This characteristic yields more effective classification power for the application areas mentioned above. Spectral Signature is nothing but a different type of materials can be represented by a set of bands, this spectral signature simplifies the separation of these materials [14] [15].

Many researchers has try to combined high spatial and spectral resolution images collected from satellite and airborne sensors, so it can be useful to improve the accuracy of detection and classification of an objects in urban areas. Many of them face challenges in obtaining accurate geo-referencing and the accuracy in change detection algorithms and spectral matching to detect anomalies in the city or town [16].

Land-use and vegetation classification is generally performed using supervised and unsupervised classification methods which are commonly available in most data processing systems. The key difference in the two methods lies in the training stage of supervised classification which involves identifying areas of specific spectral attributes for each land-cover or land-use type of interest to the analyst [12] [17] [18] [19]. In comparison unsupervised image classification into spectral classes is based solely on the natural groupings from the image values. Furthermore, remote sensing applications and specifically land-use or vegetation classification is seldom done without some form of Ground Truthing or collection of reference data. Ground-based spectral measurements are commonly done using portable, field spectrometers [20]. Field spectrometers are utilized in forestry, agriculture and other environmental studies; and the spectral signatures obtained can be used in classification and mapping of vegetation, mapping of ecosystem productivity, crop type or yield mapping, and in the detection of plant stress for water resource operations and management [12] [21].

A. Hyperspectral Data

The Remote Sensing and GIS has a very huge application. Remote Sensing data can be either of three form, Panchromatic (black and white images), Multispectral and Hyperspectral. For present research we are focusing on the Hyperspectral data analysis and its application. The Hyperspectral satellite data analysis is new research in the domain of RS and GIS [19] [22] [23].

TABLE 1: DETAIL INFORMATION OF HYPERSPECTRAL SENSOR

Types of sensors	Producer	Number of bands	Spectral range[µm]	Spatial Resolution	Swath Width	Digitization
Hyperion on EO-1	NASA Guddard Space Flight Center	242	0.40-2.50	30 m	7.75 km	12 bits
FTHSI (Fourier Transform Hyperspectral Imager) on MightySat II	Air Force Research	256	0.35-1.05	30m	7.5 km to 30 km	12 bits
AVIRIS (Airborne Visible Infrared Imaging Spectrometer)	NASA Jet Propulsion Lab.	224	0.40-2.50	20 m	11 km	10/12 bit
HYDICE (Hyperspectral Digital Imagery Collection Experiment)	Naval Research Lab	210	0.40-2.50	3 m	2.2 km	16-bit
PROBE-1	Earth Search Sciences Inc.	128	0.40-2.50	5m	1 km to 6 km	---
CASI-1500 (Compact Airborne Spectrographic Imager)	ITRES Research Limited	Over 228	0.40-1.00	25cm to 1.5m	---	20-bit
HyMap	Integrated Spectronics Australia	128	Visible to thermal Infrared	3-10m	---	---

Recent advances in remote sensing and geographic information has led the way for the development of Hyperspectral sensors. Hyperspectral remote sensing, also known as imaging spectroscopy, is a relatively new technology that is currently being investigated by researchers and scientists with regard to the detection and identification of minerals, terrestrial vegetation, and man-made materials and backgrounds. The Table .1 shows the some of the mostly used Hyperspectral Sensors with its specification [24] [25] [26] [27] [28].

B. EO-1 Hyperion Data

Hyperion is a Hyperspectral instrument on the Earth-Observing 1 (EO-1) spacecraft that was launched from Vandenberg Air Force Base on November 21, 2000. EO-1 is part of NASA's New Millennium Program, which is an initiative to demonstrate advanced technologies for dramatically reducing the cost and improving the quality of instruments and spacecraft for future space missions. Under this program, missions are intended to validate new technologies in flight and to provide useful scientific data to the user community [29] [30]. The primary demonstrations are oriented towards remote sensing technologies, and spacecraft technologies that will be used in defining future Landsat type missions. The instrument payloads on the spacecraft are Hyperion, ALI (Advanced Land Imager) and AC (atmospheric corrector). The first three months of the mission life were focused on instrument activation and performance verification [30] [31] [32].

Hyperion is a push broom, imaging spectrometer. Each ground image contains data for a 7.65 km wide (cross-track) by 185 km long (along-track) region. Each pixel covers an area of 30 m x 30 m on the ground, and a complete spectrum covering 400 – 2500 nm is collected for each pixel. Since Hyperion is a push broom system the entire 7.65 km wide swath is obtained in a single frame. The 30 m size in the along-track direction was obtained by basing the frame rate on the velocity of the spacecraft for a 705 km orbit [30] [32]. Hyperion Hyperspectral satellite data are capable of mapping the complex urban surface components of the urban land cover with accuracy similar to the higher spatial resolution airborne data [17].

C. *Problem*

Land Use / Land Cover of urban region are very complex because of the urban environments and human activities, the spatial and spectral characteristics of targets and backgrounds are extremely diverse. Because of this urban mix-structure it is very difficult to makes identify / detection and the classification of an objects. In towns, cities, and industrial areas, spatially unresolved materials are difficult to discriminate based on spectral features alone. One challenge to mapping the infrastructure of old cities is that much of the roadwork has been performed at different times and with different types of material. Remotely sensed Hyperspectral imaging allows for the detailed analysis of the surface of the Earth using advanced imaging instruments which can produce high-dimensional images with hundreds of spectral bands. This is particularly the case in urban areas, which are dominated by complex regions and surface heterogeneity which often prevents the collection of reliable ground-truth samples. While the collection of samples is generally difficult, expensive and time-consuming, by using Hyperspectral data we can identify more objects and can generate more classes [15].

III. GENERAL METHODOLOGY

Most of the research done on Hyperspectral data in the past, which mainly focused on mineral detection rather than urban surface materials such as road type etc. Because of dynamic urban development and high mapping costs, municipal authorities are interested in effective urban surface mapping that can be used for development of Smart City. The most commonly available remote sensing data for urban cover classification are LISS III, LISS IV, Thematic Mapper (TM) / Enhanced Thematic Mapper (ETM+), QuikeBird and many more. However, the former is not sufficient for accurate classification of structure and shape information, the latter is limited in the information about the spectral nature of the scene. High-resolution hyper-spectral remote sensing data (HHR) from urban areas have recently become available [30] [33] [34]. A Hyperion Images can be available and it has 242 bands, for present research we have considered a Hyperion Hyperspectral Remote Sensing data. The general methodology adopted by most of the researcher for classification of Hyperspectral image is shown in (Fig.1).

A. *Preprocessing*

In the pre-processing stage, the Hyperion data has to be gone through different processes like radiometric corrections, geometric corrections. The removal of bad bands and bad columns, then atmospheric correction of the Hyperion data has to be performed by using tools and software. To perform this task, ENVI software is widely used. There are total 242 bands are present in Hyperion data and from that bands few bands can be calibrated to nonzero. The reason for not calibrating all 242 channels is low detector response [32].

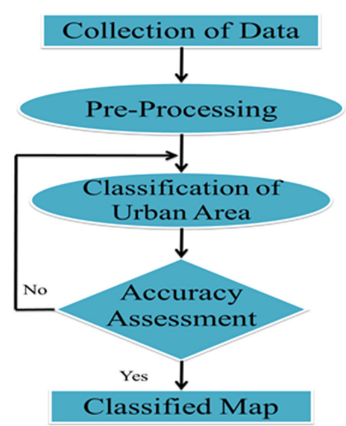

Figure 1: Methodologies for Urban Classification

B. *FLAASH*

After removal of bad bands and bad columns, the 242 bands image can be reduced. Then the Hyperion image of resized bands will be corrected for atmospheric attenuation using FLAASH model. ENVI's Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) module is a first-principles atmospheric correction modeling tool for retrieving spectral reflectance from Hyperspectral radiance images [32]. With FLAASH, you can accurately compensate for atmospheric effects.

FLAASH corrects wavelengths in the visible through near-infrared and short-wave infrared regions, up to 3 µm [35].

C. *FLAASH also includes the following features*

1) Correction for the adjacency effect (pixel mixing due to scattering of surface-reflected radiance)
2) An option to compute a scene-average visibility (aerosol/haze amount). FLAASH uses the most advanced techniques for handling particularly stressing atmospheric conditions, such as the presence of clouds.
3) Cirrus and opaque cloud classification map.
4) Adjustable spectral polishing for artifact suppression.

FLAASH supports Hyperspectral sensors (such as HyMAP, AVIRIS, HYDICE, HYPERION, Probe-1, CASI, and AISA) and multispectral sensors (such as Landsat, SPOT, IRS, and ASTER). Water vapor and aerosol retrieval are only possible when the image contains bands in appropriate wavelength positions. In addition, FLAASH can correct images collected in either vertical (nadir) or slant-viewing Geometries [32].

D. Band Combinations

While performing Classification of mix area it is very important to select a proper ban combination. Using ENVI the following is suggested for quick viewing of the Hyperion data. It should be noted that, unless you are using level 1_B data, there is a spatial offset between the Visible and Near Infrared (VNIR) and the Short Wave Infrared (SWIR). So unless the appropriate shifts are made, RGB images should be limited to only VNIR bands or only SWIR bands [30].

A simple and reliable way to get a quick feel for the contents of the image is to display a gray scale image of Band 28. This band in the VNIR corresponds to 630 nm. SWIR band 93 at 1074 nm can be used for the SWIR. The (Fig.1 (a)) shows a Panchromatic view by using Band No. 28, in this image it is clearly identified water body in white dark color but it also shows some settlement area in white color. So it can cause to misclassification. In the (Fig.1 (b)) shows a Panchromatic view using Band No. 93, it shows water in dark black color only. So by using this band it is easy to identify water bodies only. It is observed that both the Band 28 and Band 93 shows water bodies in different color. Because of this a Band combination is very much important.

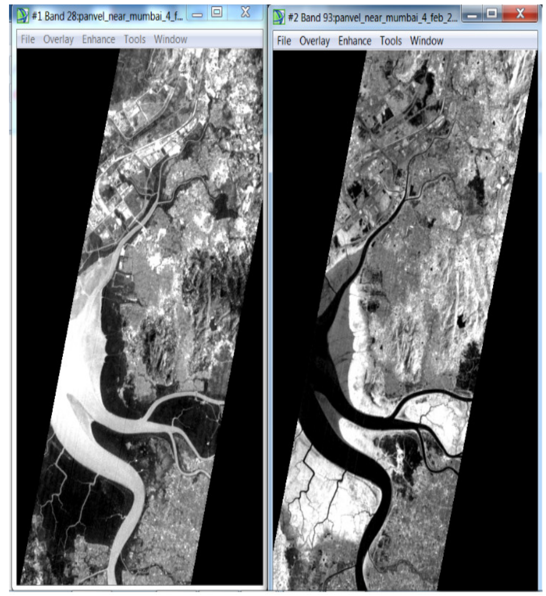

Figure 2(a): Hyperion Images With Band No 28 Figure 2(b): Hyperion Images With Band No 93

IV. CLASSIFICATION TECHNIQUES

For classifying the main categories of urban areas using Hyperspectral images, Each Classes can be detects separately and combines the detection images into a classification. These Results will be compared to those obtained from different classification techniques.

A. *Gaussian maximum likelihood*

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. It is a statistical decision criterion to assist in the classification of overlapping signatures; pixels are assigned to the class of highest probability. Gaussian Maximum Likelihood estimate of the parameters are computed and individual pixels are assigned to the class which maximizes the likelihood function of the dataset. As a pixel by pixel method this approach does not take contextual information about the neighboring classes into account in labeling a pixel. However, increased information provided by the spatial extent of the classes of the neighbors tends to mitigate the effects of noise, isolated pixels, and individual pixels [12] [16].

B. *Spectral angle mapper*

This Classifier classifies by comparing the spectral angles between the reflectance spectrum of the classified pixel and the reference spectrum obtained from training data or a spectral library [12]. Each pixel is assigned to a class according to the lowest spectral angle value. Spectral-based techniques make use of the spectral information (spectra) that can be extracted from pixels; therefore, they are also known as the pixel-based methods. Spectra can be extracted by using the standard approach, and they are processed using soft or hard classification strategies [8] [16].

C. *Parallelepiped classification*

Parallelepiped Classification is a decision rule method based on the standard deviation from the mean of each defined and trained class. A threshold of each class signature is used to determine if a given pixel falls within a class. Pixels which fall inside the parallelepiped are assigned to the class; however, those within more than one class are grouped into an overlap class. Pixels ungrouped are considered as unclassified [12].

D. *Mahalanobis Distance*

Mahalanobis distance is similar to minimum distance, except that the covariance matrix is used in the equation. Variance and covariance are figured in so that clusters that are highly varied lead to similarly varied classes, and vice versa. For example, when classifying urban areas typically a class whose pixels vary widely correctly classified pixels may be farther from the mean than those of a class for water, which is usually not a highly varied class [36].

E. *Hybrid classifier*

Hybrid Classifier is a combination of supervised and unsupervised classifier. This classification produced more accurate classifications than the supervised classification; however, it did not improve the accuracy significantly in comparison to the unsupervised classification [16] [37].

F. *PCA and Segmented PCA*

This is a Feature Reduction Methods which deals with the problem of low ratio of the number of training samples over the spectral bands and to reduce the computational cost, PC transformation is used to project the original data into a new orthogonal space with successive variance maximized [20]. The result is that the few major components contain most of the variances in the original dataset so that further analysis can be pursued based on the few major components. The SEGPCA adopts the idea of the segmented PC transformation proposed by Jia and Richards (1999) in such a way that the processing operates on subgroups of the original data rather than on the full set of data as does the conventional PCA. Thus, it further reduces the computation time and mitigates the small training problem [22] [23].

V. GROUND TRUTHING

For Ground Truthing Mobile device with GPS facility can be used to take exact ground values, it can give 4 m accuracy. Also Field Spectra device can be used to collect different Urban Land Use and Land Cover Area. A Spectro-radiometer can be used for measurements of surface reflectance of urban area's samples. All the spectral measurements of urban area have to be collected during noontime to avoid the impact of illumination changes on the spectral responses. During data acquisition, the sensor has to be first placed over the reference panel to record the panel-reflected radiance [24]. A spectral library of pure urban materials and different types of vegetation will be created for the urban area and it will be taken up for further processing. Ground spectral profiles collected using Spectro-radiometer, can be used as reference spectrum to validate classification results [20] [29].

VI. ACCURACY ASSESSMENT

There are different techniques are used for Accuracy assessment of the result of Classification. An Overall Accuracy (OA) which is the number of well classified samples divided by the number of test's samples. An Average Accuracy (AA) which represents the average of class classification accuracy. A Kappa Coefficient of agreement (ƙ) which is the percentage of agreement corrected by the amount of agreement that could be expected due to chance alone. These criteria were used to compare classification results and were computed using the confusion matrix [38] [39].

VII. CONCLUSION

Hyperspectral images can provide a large amount of detailed information as compared to high spatial resolution and can be used in the mapping of urban areas. Conventional methods use only either spectral information or spatial information to classify such imagery. To improve these methods, spatial information will need to be used together with spectral information, as urban areas have a complex mix of manmade and natural features. Techniques utilizing both spectral and spatial components of Hyperspectral data should be adopted if the full potential of Hyperspectral data is to be exploited. However, this is not an easy task, as the methodology is challenging but this kind of work can be used to design and develops a Smart City concept.

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