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COMPARATIVE STUDY OF OBJECT BASED IMAGE ANALYSIS ON HIGH RESOLUTION SATELLITE IMAGES FOR URBAN DEVELOPMENT

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***Abstract* — For land cover classification and urban area analysis remote sensing techniques are gaining more importance. Numerous remote sensing techniques have been developed for analyzing the satellite images. The launch of Worldview-2 satellite with resolution of 0.5 m signaled the advent of high resolution satellite images. Such images offer an exciting possibility for feature extraction as well as complex land cover classification. The most suitable approach for analysis of high resolution satellite images is Object based Image Analysis (OBIA). OBIA is relatively new class of algorithm that have been developed to focus not only on the spectral properties of features but also spatial such as their shape, orientation, texture, contextual relation feature and so on. In this study, authors have used WV-2 image and classification is carried out with two approaches. First method is based on rule set approach where domain expert knowledge is represented in rules with Cognition network language whereas second approach is Nearest Neighbor (NN) classification. Accuracy of classification carried out with the help of confusion matrix which indicates that rule based classification is more accurate as compare to NN. However for complex land like urban area both approaches are suitable as compare to pixel based approach.**

***Keywords* — High resolution Images, OBIA, Multiresolution segmentation, World view-2, urban area, NN classification**

I. INTRODUCTION

The detail and accurate land cover mapping is need of most of the municipalities, government organizations, environmental science institutes to monitor or for decision making purpose. To fulfill this need remote sensing data is most reliable and updated as compared to field survey methods. The new generation of high spatial resolution satellites, starting with IKONOS in 1999 and followed by Quickbird in 2001, WorldView-2 (WV-2) in 2009, WV-3 in 2014 produced tremendous change in remote sensing. These high resolution satellite images from different platforms represent valuable information which can be utilized for preparing maps in GIS applications. Many studies have been carried out to find out an appropriate method to classify remote sensing data. The analysis of such images is mostly carried out with pixel based classification which primarily focuses on the spectral properties of pixel. However these classification methods are more suitable for images whose spatial resolution is too coarse to detect individual features on a given landscape. Pixel by pixel methods are slower also leads to noise influence sensitivity, uncertainty of mixed pixels, low efficiency etc.

The failure of pixel based techniques is due to the fact that these are based on assumption that individual classes contain uniform visual properties. As the special resolution of data is increased the intra-class variation increases and the property of class uniformity is broken leading to very poor performance. For high resolution satellite images pixel based classification approach results in less accuracy as well as it leads for salt and pepper effect. Hence a new paradigm called object based image analysis is introduced to process the high resolution images. Instead of single pixel it focuses on group of pixels that constitute an object [1]. These objects give more information such as geometrical, textural, contextual, positional etc.

There are three building blocks of OBIA approach - segmentation, feature extraction and classification. Each object on the earth has unique reflectance pattern as a function of wavelength. Meaningful objects are created with segmentation algorithms which replicate the spectrally homogeneous land cover type and pixels having heterogeneous reflectance. There are different segmentation algorithms available. The objects have their distinct features which help in classification process. The most significant feature must be selected to assign the object to proper class. Classification can also be done with several methods like NN, Support vector machine (SVM), Artificial Neural networks (ANN) etc.

II. STUDY AREA AND IMAGE DATA

In this work, WorldView-2 imagery of urban area of Mumbai City, acquired in November 2010 is considered. Very high spatial resolution of WV 2, combined with the increased spectral fidelity provides additional data which is necessary for classification of complex landscape. The image has radiometric resolution of 11 bits. There are 9 spectral bands in WV-2 imagery. One panchromatic band with spacial resolution of 0.5 meters and the 8 multispectral bands with resolution of 2 meters. Pansharpening uses spatial information in the high resolution gray scale band and color information in multispectral band to create single high resolution color image. Pansharpening is also called as resolution merging. The image is pansharpened with Hyperspherical color space (HCS) resolution merge technique in Erdas imagine software. WV-2 is the first high resolution satellite imagery with 4 new bands in addition to RGB and NIR.

Coastal Band (400 - 450 nm) - This band is used to investigate atmospheric correction techniques. It gives chlorophyll and water penetration characteristics hence useful in bathymetric studies.

Yellow Band (585 - 625 nm) - Used to identify "yellow-ness" characteristic of target. This band will assist in the development of "true-color" hue correction for human vision representation.

Red Edge Band (705 - 745 nm) - This band is mostly used to analyze plant health, plants diseases.

Near Infrared (IR) 2 Band (860 - 1040 nm)- This band overlaps the NIR 1 band but is less affected by atmospheric influence. It supports vegetation analysis and biomass studies [2,3].

Image used in this study comprises of a buildings, a quarry site, river, roads, vegetation and trees *etc*. Urban landscapes are a unique combination of natural and built environments. There is relatively high local variance due to that it is challenging task to classify the image.

III. METHODOLOGY

Expert system in an OBIA environment must employ an iterative approach that mimics human analytical process. This involves repeated segmentation, classification and refinement of image object until the desired land cover classification is achieved. Such an approach effectively incorporates the elements of manual image interpretation and essentially translates the procedure used by human analyst into series of rules. Authors have evaluated the method of image classification with two approaches rule set method and Nearest neighbor (NN) classification [4].

The powerful functionality of eCognition is that it can create the objects with different scale parameters and at different levels. A typical image is comprised of features of various sizes. Higher scale parameter values produces large objects, so if those objects are homogeneous will be extracted at higher level itself whereas for heterogeneous areas they are segmented further with smaller scale parameter values to get detailed objects [5].

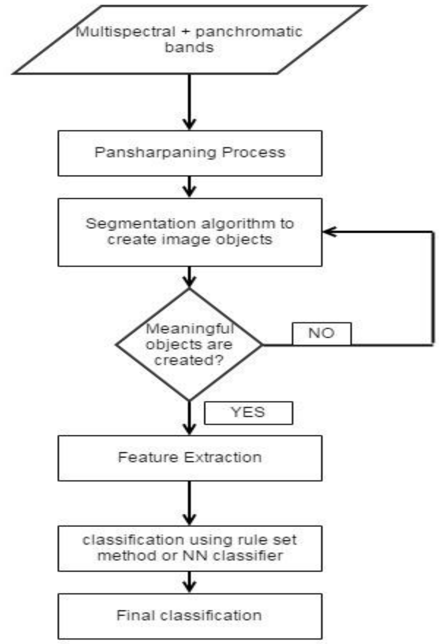

Fig. 1 Methodology used for Object based classification

A. *Rule set method:*

Segmentation process creates new image objects or alters the morphology of existing image objects according to specific criteria. The selection of proper segmentation algorithm with suitable scale helps in accurate classification process. Multiresolution segmentation (MRS) is one of the most appropriate segmentation approach for high resolution images. It is bottom up segmentation algorithm consecutively merges the pixels depending on heterogeneity criteria. The heterogeneity criterion is combination of compactness and shape properties of initial and resulting object of intended merging. Shape criterion determines the influence shape compare to color whereas compactness gives its relative weighting against smoothness [6,10].

Level 1 is created with multiresolution segmentation, with scale parameter 200, shape and compactness parameters 0.2 and 0.7 respectively. Also band weights are kept high for Red and NIR band so that more values will be given to those while creating objects. At Level 1image is classified at 3 classes ‘Vegetation’, ‘water’ and ‘urban land’. False color composition (FCC) is most preferred for analysis of vegetation as vegetation has more reflectance in NIR bands [8]. Different indices are used for classification such as LWM (Land and water mask) for water, NDVI (Normalized difference vegetation index) for vegetation extraction formula for them given below :

$$\text{LWM} = \frac{\text{NIR 1}}{\text{Green}} \quad (1)$$

$$\text{NDVI} = \frac{\text{NIR 1} - \text{Red}}{\text{NIR 1} + \text{Red}} \quad (2)$$

Fig. 2 True color imagery of dataset

Fig. 3 False color composite of image with primary segmentation

Vegetation area is extracted with thresholding on NDVI but some small area of vegetation is classified as urban land class. To extract that NDVI is created as a separate layer at Level 2 and contrast split applied only on urban area. This gives small area of vegetation as separate object. Contrast split is top down segmentation algorithm which can be applied only on 1 layer. Also shadow area is classified at level 2, those area having low intensity value as well as NIR bands spectral reflectance is very low. Hence contrast split applied on NIR band and lower values assigned to shadow class [6].

Building detection is one of the most basic tasks in most of the aforementioned urban applications. In the image the building are very bright but that can not be true for all the areas. Another way of extracting buildings can be with the help of edges. Built up areas are having more spectral visibility for edges as compare to other areas. For edge extraction canny's algorithm is used and separate edge layer is created. At level 3, on the remaining urban area MRS is applied with scale of 100, more weight assigned to edge layer so that proper building objects can be created. Shape and compactness parameters are 0.2 and 0.7 respectively. Contextual features, brightness, edge layer values are applied to classify the building in an image. Other part of the image is classified as slum area comprises of very small houses in much more congested way [9].

B. NN Classification method:

Nearest neighbor classification in eCognition is supervised classification. Where the training area for each class is defined based on prior experience with area or knowledge of image interpretation. Such training areas are referred to as samples or sample objects. After defining the samples the other unknown image objects are classified based on closest training samples in the feature space. Typically finding NN is based on the Euclidean or Mahalanobis distance function. Successful nearest neighbor classification requires several rounds of sample selection and classification.

Feature space optimization is one more popular approach which provides the most suitable combination of features for separating classes, in conjunction with a NN classifier. Various bands mean values, standard deviation of bands, intensity, area, density, shape features, customized features such as indices are given out of which few those are best suitable are selected. The number of features are also called as dimensions. Class separation distance matrix is also calculated for selected features. This matrix shows the distances between samples of the selected classes within selected feature space. Area, density, rectangular fit, LWM, GRVI (Green red vegetation index) this are the five features selected by feature space optimization with best separation distance of 1.024 for study area [7].

$$\text{GRVI} = \frac{\text{Green} - \text{Red}}{\text{Green} + \text{Red}} \quad (3)$$

Class separation distance matrix is given in Table. Further information about all feature combination and the separability of the class samples are given in figure 4.

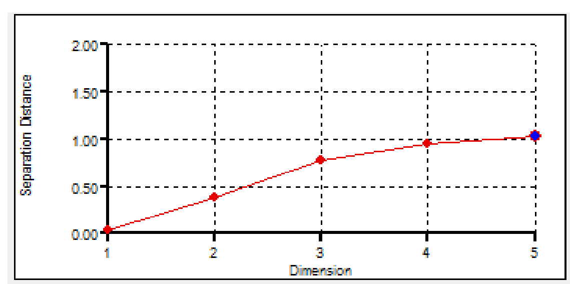

Fig. 4 Feature space optimization with different dimensions

TABLE I
Class Separation Distance Matrix for Selected features

Class/Class	Water	vegetation	Shadow	Buildings	open space	slum area
Dimension: 5						
Water	0	9.81	4.082	9.489	7.204	4.73
vegetation	9.81	0	3.961	5.011	4.588	4.464
Shadow	4.082	3.961	0	3.905	3.259	2.071
Buildings	9.489	5.011	3.905	0	1.595	1.982
open space	7.204	4.588	3.259	1.595	0	1.032
slum area	4.73	4.464	2.071	1.982	1.032	0

TABLE II
Confusion Matrix for Rule Based System

User Class \ Sample	Water	Vegetation	Shadow	Buildings	Open space	Slum area	Sum
Water	4	0	0	0	0	0	4
Vegetation	0	18	0	0	0	0	18
Shadow	1	0	17	0	0	0	18
Buildings	0	0	0	20	1	2	23
Open space	0	0	0	0	12	0	12
Slum area	1	0	4	0	1	19	25
Sum	6	18	21	20	14	21	100
Producer's accuracy	0.6666	1	0.8095	1	0.8571	0.9047	
User's accuracy	1	1	0.9444	0.8695	1	0.76	

Overall accuracy = 0.9 KIA = 0.876

TABLE III
Confusion Matrix for NN Classification

User Class \ Sample	Water	Vegetation	Shadow	Buildings	Open space	Slum area	Sum
Water	5	0	0	0	0	0	5
Vegetation	0	19	0	0	0	0	19
Shadow	1	1	18	0	1	0	21
Buildings	0	0	0	19	0	0	19
open space	0	0	0	4	15	5	24
slum area	0	2	0	3	2	13	20
Sum	6	22	18	26	18	18	108
Producer's accuracy	0.8333	0.8636	1	0.7307	0.8333	0.7222	
User's accuracy	1	1	0.8571	1	0.625	0.6842	

Overall accuracy = 0.824 KIA = 0.785

IV. RESULTS AND DISCUSSION

As the remotely sensed information products are increasingly used in decision making applications accuracy assessment of classification result is one of the critical task. The level of correctness of the results of classification is evaluated by accuracy assessment through the confusion matrix. Confusion matrix is also known as error matrix which shows the comparison of thematic

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classes with reference or sample data. Others terms which measures the accuracy thematic map derived from multispectral imagery are and determining the percentage of correct predictions for these samples [11].

However user's accuracy is computed by looking at the predictions produced for a class and determining the percentage of correct predictions.

Table1.listed above gives a summary of accuracy and error statistics of the two classification approaches. As seen in the above images the output of Object based classification is more smooth and coherent as compare to pixel based classification. It is evident that regions are misclassified with NN approach. For example most of the shadow regions are classified as water this is due to similar spectral response of shadow and water. If some contextual features will be applied that can be properly classified. The combination of NNand ruleset method can give much proper results instead of NN alone.

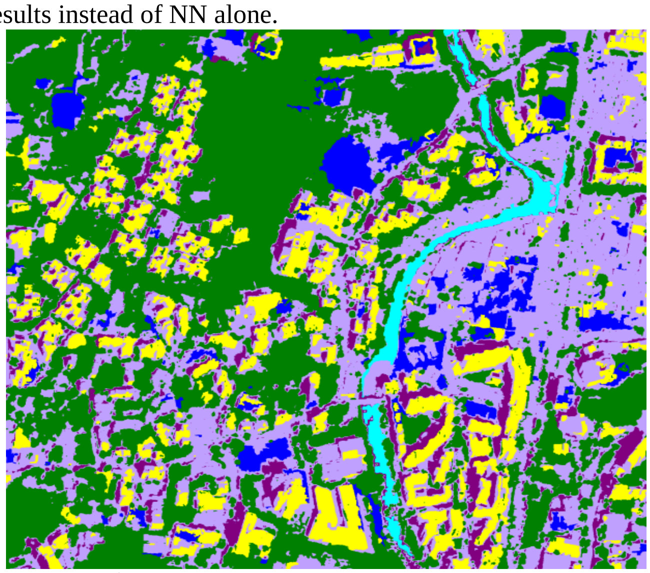


Fig. 5 Classification with rule set method

producer's accuracy and user's accuracy. Producer's accuracy is computed by looking a reference data for a class

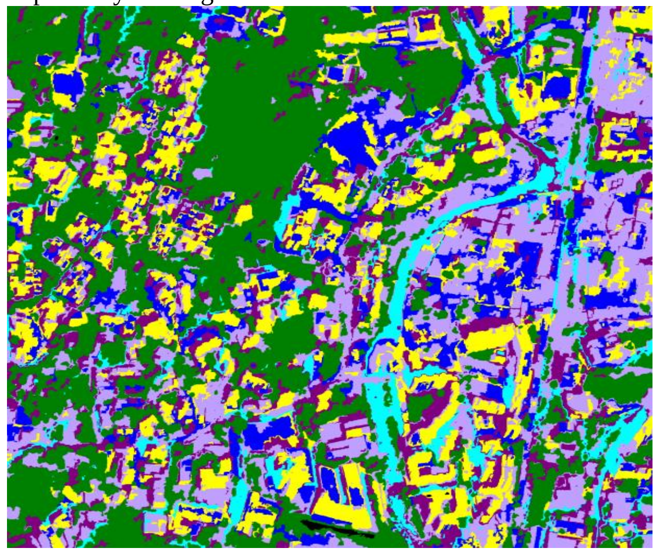
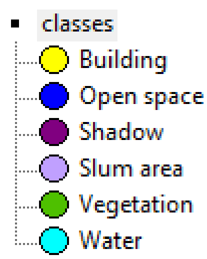


Fig. 6 Classified image with NN mehod



V. CONCUSION

The growing demands for accurate land cover maps especially for complicated and heterogeneous urban area can be fulfill by OBIA approach and high resolution images. Class descriptions and segmentation parameters developed for one area can be transformed to other easily with minor adaptations. OBIA technique for image classification not only provides higher accuracy but also operational simplicity, time efficiency, effectiveness of replicating human visual system associated with it made it more popular. Results indicated that the object based approach provided flexible and effective means to integrate high resolution data for urban land cover classification which is superior to pixel based approach. The results can be made more accurate with LIDAR data which provides height and intensity data with the help of such data trees and grassland, towers and small buildings can be accurately classified. The change in urban area can also be extracted accurately with OBIA paradigm and ancillary data.

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