AN EFFICIENT APPROACH FOR EXTRACTION OF LINEAR FEATURES FROM HIGH RESOLUTION INDIAN SATELLITE IMAGERIES

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***Abstract*— This paper presents an Object oriented feature extraction approach in order to classify the linear features like drainage, roads etc. from high resolution Indian satellite imageries. It starts with the multiresolution segmentations of image objects for optimal separation and representation of image regions or objects. Fuzzy membership functions were defined for a selected set of image object parameters such as mean, ratio, shape index, area etc. for representation of required image objects. Experiment was carried out for both panchromatic (CARTOSAT-I) and multispectral (IRSP6 LISS IV) Indian satellite imageries. Experimental results show that the extraction of linear features can be achieved in a satisfactory level through proper segmentation and appropriate definition & representation of key parameters of image objects.**

Keywords- Object oriented; Multireslution segmentation; Image objects; Homogeneity criterion; Fuzzy membership functions.

I. INTRODUCTION

Recent researches on image classification have shown that conventional 'hard' classification techniques, which allocate each pixel to a specific class, are often inappropriate for applications where mixed pixels are abundant in the image [1]. A major drawback found for these traditional parametric classifiers is that they require training data to be normally distributed [2]. Typically, they have considerable difficulties dealing with the rich information content of high resolution data; they produce a characteristic, inconsistent classification, and they are far from being capable of extracting objects of interest.

The development and application of new classification techniques is currently a highly important research area and application issue [3]. Non-parametric classifiers such as neural network, decision tree classifier etc. are becoming important approaches for multisource data classification [4]. Recently, Scientists are attracted towards the development of improved classification algorithms which are mainly falling under 'soft' classification category. Object oriented classification is treated as one of the most important approaches under this category. Here, classification is not only based on single pixel information, but of entire objects into which the information content is distributed. Some of the approaches are hybrid; comprised of both pixel and object based analysis and can give significantly satisfactory results in case of aerial imageries also. Even small wooded elements in rural landscape from aerial photography could be discriminated [5]. In Definiens Software (eCogntion), object oriented classification analysis is realized through a series of image segmentation processes, known as multiresolution segmentation. However, many issues still need to be researched to handle the high resolution satellite data. Automatic extraction of linear features like roads, drainage and manmade objects like buildings etc. from high resolution satellite data is not a simple task. Because, difficulty lies in the high misclassification between roads and other spectrally similar objects, such as parking lots, buildings or crop fields [6].

II. DATA USED

The work presented here is for two different types of terrain data in order to see the variation of classification accuracy. Orthorectified Cartosat-I PAN (Panchromatic) and IRS P6 LISS IV MX (multispectral) data were used (Table I).

TABLE I. SPECIFICATION OF DATA

Sensor	Yr	Mode	Pixels sized	Resolution		
				Rad (bit)	Spec (µm)	Spa (m)
CARTOSAT-1 (Plain & hilly terrain)	2007 2008	PAN	12000x 12000	10	0.5-0.85	2.5
IRS P6 LISS IV (Plain & hilly terrain)	2007 2008	MX	12288x 12288	11	0.5-0.6 (B)	5.8
					0.5-0.62 (G)	
					0.5-0.62 (R)	
					0.5-0.62 (IR)	
Yr: Year; Rad: Radiometric; Spec: Spectral; Spa: Spatial						

Green (G), red (R) and infrared (IR) bands were used in case of multispectral images, because information contents (reflectance) are rich in these spectral bands.

III. APPROACH

Our approach is an object oriented feature extraction approach which relies on multiresolution image segmentation and uses soft classifier. In this work, it was attempted to investigate the list of key parameters of image objects for linear objects representation and a set of such parameters were computed and properly defined using fuzzy membership functions.

A. Multiresolution image segmentation

It is a bottom up region growing technique starting with one pixel objects, merging process will continue until the user specified criteria is reached [7]. Two modes of segmentation were used; one is based on spectral or colour and spatial (shape) homogeneity criterion and another one is based on sub object line analysis and both the modes were fixed by a scale parameter 'S'. Scale determines the maximum allowed heterogeneity for the resulting image objects. Scale in every segmentation determines the magnitude or the level of abstraction on which a certain phenomenon can be described. Here, segmentation was carried out up to L2 based on colour and shape homogeneity criterion with distinct weights assigned to the necessary parameters during segmentation process.

Spectral and shape homogeneity criteria are computed for L1 and L2 segmentations using the following equations (eCognition):

$$H_{spectral} = \sum W_L \sigma_c \quad (1)$$

Spectral or colour homogeneity $H_{spectral}$ is the sum of the standard deviations σ_c of spectral values in each layer of multispectral images weighted with the weights W_L for each layer.

$$H_{shape} = W_{comp} H_{comp} + W_{sm} H_{smooth} \quad (2)$$

The shape criterion H_{shape} is associated with two of its sub criterion i.e. compactness, H_{comp} and smoothness, H_{smooth} along with the defined weights i.e. W_{comp} and W_{sm}.

$$F = W_c H_{spectral} + W_{sh} H_{shape} \quad (3)$$

F is the overall fusion value where W_c and W_{sh} are weights assigned to the $H_{spectral}$ and H_{shape} respectively.

L3 sub object line analysis segmentation was carried out in order to create sub objects for the calculation of line features based sub objects. It takes the borders of super objects into consideration, producing compact sub objects (eCognition). The scale parameter in this mode ranges from 0.5 to 1.

The values of scale parameters and weights assigned during multiresolution segmentation are shown in the following Tables (II-III).

TABLE II. SEGMENTATION INPUTS FOR CARTOSAT-I IMAGES

Case	Level	S	W_L	W_{comp}	W_{sm}	W_c	W_{sh}
Case-1 CARTOSAT (Plain area)	L1	25	1	0.4	0.6	0.7	0.3
	L2	55	1	0.5	0.5	0.6	0.4
	L3	0.7	-	-	-	-	-
Case-2 CARTOSAT (Hilly area)	L1	35	1	0.5	0.5	0.8	0.2
	L2	45	1	0.5	0.5	0.7	0.3
	L3	0.6	-	-	-	-	-

TABLE III. SEGMENTATION INPUTS FOR IRS P6 LISS IV IMAGES

Case	Level	S	W_L	W_{comp}	W_{sm}	W_c	W_{sh}
Case-3 IRSP6 (Hilly area)	L1	25	1	0.3	0.7	0.7	0.3
	L2	34	1	0.2	0.8	0.8	0.2
	L3	0.5	-	-	-	-	-
Case-4 IRSP6 (Plain area)	L1	35	1	0.7	0.3	0.8	0.2
	L2	45	1	0.4	0.6	0.7	0.3
	L3	0.7	-	-	-	-	-

B. Object oriented classification

Once, the image objects were formed to a satisfactory level, then it uses most powerful 'soft classifiers' based on fuzzy systems for class representation and description of image objects. The image objects are characterized with suitable features parameters according to the classes we wanted to extract. Fuzzy membership functions were defined on these parameters values for fulfilling an object to be assigned to a particular class. Values of these selected parameters of individual image object may be computed as per the following equations (eCognition):

$$\mu_L = \frac{1}{n} \sum_{i=1}^{n} \mu_{L_i} \quad (4)$$

Layer mean (μ_L) is calculated from the layer values of all n pixels forming an image object.

TABLE IV. KEY OBJECT FEATURES FOR CLASS DEFINITION

Case	Level	Object class hierarchy	Object features (for fuzzy membership functions)
CARTOSAT-I	L1	Object of interest, Others	Mean, Brightness, Area
	L2	Linear, Nonlinear	Area , Shape Index , Line-to-Width ratio, Border length
	L3	Road, drainage, Rail road	Area , Shape Index , Line-to-Width ratio, Length (line so)
IRSP6 LISS IV	L1	Object of interest, Others	Mean, Brightness, Ratio, Area
	L2	Linear, Nonlinear	Area , Shape Index , Line-to-Width ratio, Length (line so)
	L3	Road, Drainage	Ratio, Area , Shape Index, Line-to-Width ratio, Length (line so)

$$b = \frac{1}{n_L}\sum_{i=1}^{n_L}\mu_i \quad (5)$$

Brightness (b) is the sum of mean values of the layers containing the spectral information divides by their quantity computed for an image object.

$$r_L = \mu_L / \sum_{i=1}^{n_L}\mu_i \quad (6)$$

Ratio (r_L) is the ratio of mean value of a layer of an image object divided by the sum of all spectral layer mean values.

$$s_I = \frac{e}{4\sqrt{A}} \quad (7)$$

Shape Index (s_I) is the border length e of the image object divided by $4\sqrt{A}$, where, A is the area of an image object which is nothing but the number of pixels forming it. The border length e of an image object is defined as the sum of edges of the image objects that shared with other image objects.

Line-to-Width ratio (γ) can be derived from bounding box estimation. The main information provided by the bounding box is its length a, its width b, its area a*b and its degree of filling f which is the area A covered by the image object divided by the total area a * b of the bounding box.

$$\gamma = \frac{a^2 + ((1-f)b)^2}{A} \quad (8)$$

$$L_{so} = r_1 + r_2 + \sum_{i=1}^{n} d_i \quad (9)$$

Length/line so (L_{so}) is shape of an object may be represented by compact sub objects and operate from center point to center point to get line information, where, d_i is the distance between the centre points of adjacent sub objects and r_1 & r_2 are the radii of the end objects.

The class hierarchy was defined as per the segmentation levels as shown in the Table IV. In the L1 segmentation level, we have defined two classes of surface area: Object of interest and other objects. Object of interest class contains the probable required image objects based on mean, brightness, ratio, area etc. values. In the L2 segmentation level, object of interest class was classified down to the two child classes; linear and nonlinear. Since, the aim of this study is to extract only linear features of satellite images only, hence the linear class was further classified to road, drainage and rail road in case of CARTOSAT-I satellite imageries and road and drainage in case of IRS P6 LISS IV satellite imageries in L3 segmentation. In this manner, all the object features characteristics were inherited from L1 & L2 to L3 for better discrimination of classes having similar spectral characteristics using fuzzy membership functions.

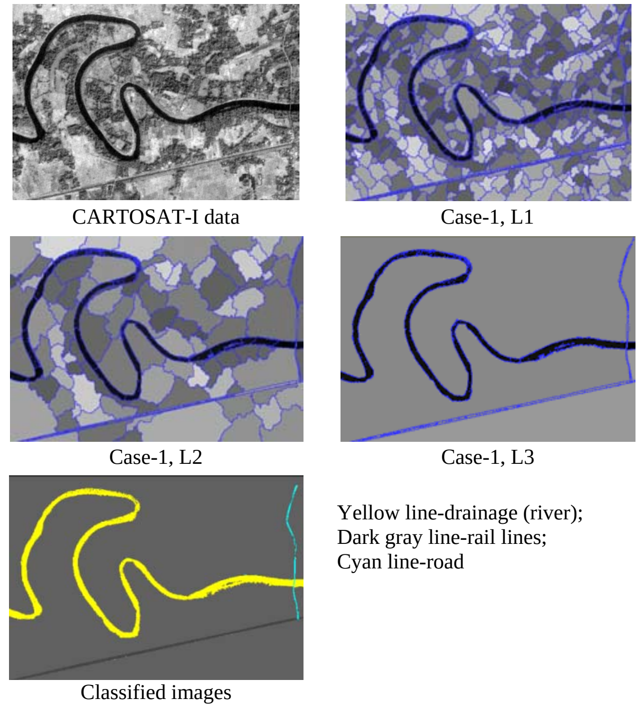


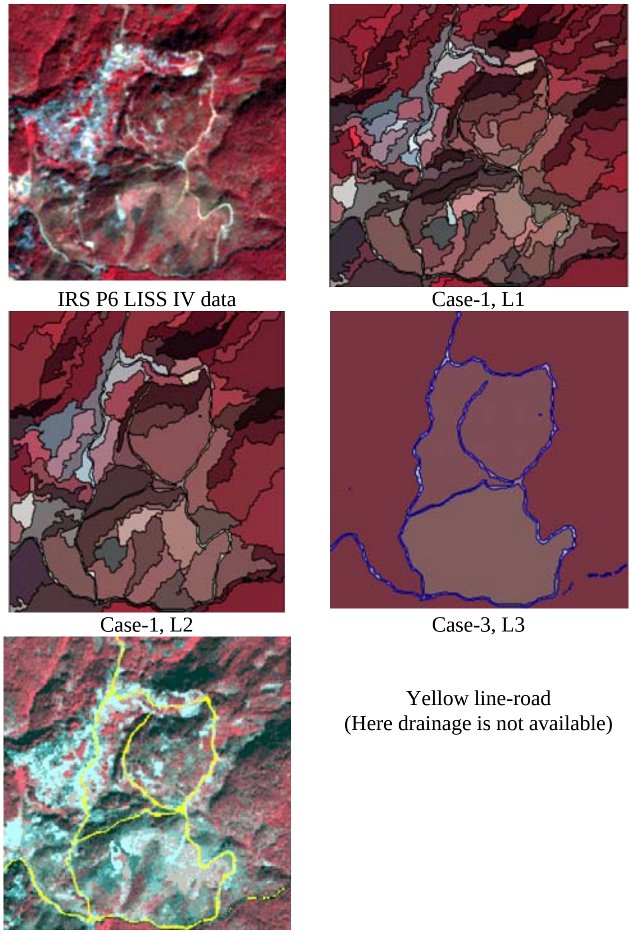
Figure 1. Segmentation and classification for CARTOSAT-I images

IV. EXPERIMENTAL RESULTS

The first step of segmentation algorithm is one of the most important steps. Because, it determines the range of segmentation parameters for optimal separation of image objects. It is observed from the experimental results that the suitable range of scale parameter is 25-55 (L1-L2) in case of CARTOSAT-I data and 25-45 (L1-L2) in case of IRS P6 LISS IV data (Tables II-III). The potential range of scale parameter of segmentations can be computed by analyzing the spectral relationships between the neighboring objects. Sub object line analysis mode of segmentation (L3) could properly form the linear objects of interest. Segmentation results are highly affected by the assigned weights also. These weights can be same for both hilly and plain area data. Few test results are presented in the Figures (1-2).

Linear features like roads, drainage etc. may not be prominently visible in hilly terrain because of terrain condition, atmospheric or other sensor related problems. It was a challenge for the segmentation algorithm for creation of image objects of interest. Some portions of road segments could not be recognized and classified from other objects. Sometimes, it may so happen that the spectral reflections of unmetalled roads are almost similar to the river bed. Similarly, same thing happened while trying to separate out metalled roads from the dry river. Separation of roads from river or roads from railway line can be possible only when segmentation takes place on different scale parameters.

An assessment was carried out using error matrix approach for the evaluation of classification algorithm under different terrain conditions.



IRS P6 LISS IV data

Case-1, L1

Case-1, L2

Case-3, L3

Classified images

Yellow line-road
(Here drainage is not available)

Figure 2. Segmentation and classification for IRS P6 LISS IV images

Around 25 points were selected randomly for each of the classes and compared with the IKONOS (PAN, 1m spatial resolution) satellite data. Kappa analysis is recognized as a powerful method for analyzing a single error matrix and for comparing the differences between various error matrices [8]. Kappa statistic is a measure of the difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and a random classifier.

Kappa coefficient is defined as [9]:

$$\hat{K} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}\left(X_{i+}X_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(X_{i+}X_{+i}\right)} \qquad (10)$$

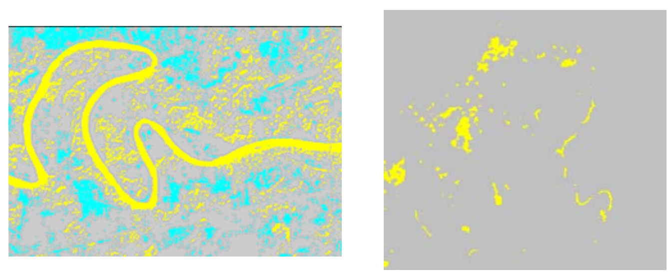
Where, r is the number of rows in the error matrix, X_{ii} is the number of observations in row and column, Xi+ and X+i are total of observations in row i and column i respectively. N is total number of observations included in the matrix. In reality, kappa coefficient usually ranges from 0 to 1.

For example, a value of kappa coefficient of 0.7802 can be thought of as an indication that an observed classification is 78 percent better than one resulting from chance. Table V shows that the classification accuracy is much higher in case of CARTOSAT-I data under plain terrain condition. Overall accuracy is significantly lower in case of IRS P6 LISS IV data (hilly terrain).

TABLE V. ACCURACY ASSESSMENT

Sensor	Terrain	Kappa coefficient
CARTOSAT-I	Plain area	0.7802
IRS P6 LISS IV	Plain area	0.7283
CARTOSAT-I	Hilly area	0.7479
IRS P6 LISS IV	Hilly area	0.6344

In this study, extraction of linear features was carried out utilizing a supervised maximum likelihood classification technique on the same set of datasets in order to compare the results with our approach. But the results from this widely used pixel based classifier technique were not satisfactory. Road and railway lines could not be discriminated and drainage was extracted out but some of the other land features were also classified as drainage in case of CARTOSAT-I data (Figure 3). In case of multispectral images, some of the other land cover features such as urban settlements were wrongly classified as road because of similar spectral characteristics. It again reveals the limits of multispectral classification at the pixel level for the classification of very high resolution images [10]. Of course, assessment of satellite classification accuracy is also highly dependent upon the reference datasets [11].



CARTOSAT-I classified data

IRS P6 LISS IV classified data

Figure 3. Results from maximum liklihood classifier

From the experiments it has been observed that appropriate representation of area, shape index, line/width, length (line so) parameters have a crucial role in discriminating the classes in case of any high resolution data such as CARTOSAT-I images. Apart from these, proper fuzzy membership definitions of mean, ratio, brightness parameters also can improve the accuracy in case of IRS P6 LISS IV data.

CONCLUSION

This paper presents our work on extraction of linear features like roads, drainage etc. from high resolution Indian satellite imageries. Multiresolution segmentation followed by an object oriented classification is found to be an efficient approach for this purpose. It also demonstrates that the overall classification accuracy could be improved by appropriately defining the fuzzy membership functions of object parameters.

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REFERENCES

[1] G.M. Foody, "Land cover mapping from remotelysensed data with a neural network: accommodating fuzziness,", 1st COMPARES Workshop, York, UK, 1996.

[2] J.R. Jensen, "Introductory Digital Image Processing: a Remote Sensing Perspective,", 2nd Edition, Prentice Hall, Upper Saddle River, pp. 197-256, 1996.

[3] S. Lewinski, and K. Zaremski, "Example of Object-Oriented classification performed on high-resolution satellite images,", Miscellanea Geographica, Warszawa, Vol.11, pp.349-358, 2004.

[4] D. Lu, and Q. Weng, "A survey of image classification methods and techniques for improving classification performance,", Int. Journal of Remote Sensing, Vol.28, No.5, pp.823-870, 10 March, 2007.

[5] D. Sheeren, N. Bastin, A. Oun, S. Ladet, G. Balent and J.P. Lacombet, "Discrimininiting small wooded elements in rural landscape from aerial photography: a hybrid pixel/object-based analysis approach,", In the Int. Journal of Remote Sensing, Vol.30, No.19, pp.4979-4990, 10 Oct, 2009.

[6] P. Doucette, P. Agouris, and A. Stefanidis, "Automated Road Extraction from High Resolution Multispectral Imagery,", Journal of Photogrammetric Engineering & Remote Sensing, Vo.70, No. 12, pp. 1405–1416, December 2004.

[7] M. Baatz and A. Schape, "Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation,", In the 12th Angewandte Geographische Informationseverarbeitung (Karlsruhe: Herbert Wichmann Verlag), pp.12-23, 2000.

[8] R. Congalton, "A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data,". Journal of Remote Sensing of Environment, Vol. 37: pp. 35-46, 1991.

[9] J.R. Jensen, "Introductory Digital Image Processing: a Remote Sensing Perspective,", 2nd Edition, Prentice Hall, Upper Saddle River, pp. 590-591, 2007.

[10] A. Carleer and E. Wolff, "Exploitation of Very High Resolution Satellite Data for Tree Species Identification,", Journal of Photogrammetric Engineering & Remote Sensing, Vol. 70, No. 1, pp. 135–140, January 2004.

[11] M. S. Ismail and K. Jusoff, "Satellite Data Classification Accuracy Assessment Based from Reference Dataset,", In the Int. Journal of Computer and Information Science and Engineering, Vol. 2, No. 1, pp.96-102, 2008.