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Implementation of Statistical Region Merging and Texture Analysis of Hyperspectral Remote Sensing Data

Spoorti Rajeev Kulkarni[1], Arvind Kumar Singh[2], and Venu K. N[3]
[1]M.S. Ramaiah Institute of Technology, Bangalore, India
Email: spoortikulkarni93@gmail.com
[2]ISRO Satellite Centre, Bangalore, India
Email: arksingh@isac.gov.in
[3]Assistant Professor, M.S. Ramaiah Institute of Technology, Bangalore, India
Email: venu1.kn@msrit.edu

***Abstract*— Remote sensing is an area of science in which information about objects or areas from a distance, typically from aircraft or satellites are obtained. Many approaches for studying hyperspectral images focus on the spectral information in individual image cells, rather than spatial distinctions within individual bands or groups of bands. The objective of the undertaken work is to exploit segmentation based Statistical Region Merging algorithm and conduct Texture Analysis for the spatial-spectral classification of hyperspectral images.**

***Index Terms*— Remote Sensing, Hyperspectral Imaging, Statistical Region Merging, Classification, Texture Analysis.**

I. INTRODUCTION

Hyperspectral remote sensing systems use sensors that operate from the visible through the infrared wavelength ranges and can concurrently capture hundreds of narrow spectral bands from a given area on Earth's surface. Hyperspectral images consist of hundreds of spectral data channels of the same scene. The detailed spectral information provided by hyperspectral sensors yield in the accurate discrimination of materials of interest with increased classification accuracy [1]. The Hughes phenomenon / curse of dimensionality pose a problem for designing robust statistical estimations. In order to make the most of the information provided by the hyperspectral data, Principal Component Analysis (PCA) is used [8]. Thus, PCA is an apt technique for dimensionality reduction of hyperspectral images.

The objective is to implement segmentation and classification technique for hyperspectral remote sensing image. This work focuses on the statistical method of image segmentation, region growing and region merging techniques. Region merging techniques use statistical test to decide the merging of regions. The Statistical Region Merging (SRM) algorithm has an optimal time and space complexity. It does not depend on the distribution of the data and has an excellent performance in handling data with significant noise corruption [9]. The scope of the undertaken work is to successfully segment the Buildings from the different classes including Roads, Trees, Land, Water and Grass in the Hydice Washington-DC hyperspectral image (Courtesy: Multispec) which is achieved using Texture Analysis. The ambiguity in the spectral signatures of

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roads and buildings make it hard to completely segment the two classes. For this purpose, texture analysis is implemented, which considers the Variance, Entropy, and Homogeneity between the pixels and gives the desired separation between the two classes.

In 2004, Nock, Richard and Nielsen proposed the Statistical Region Merging algorithm. It is a robust segmentation technique with deterministic results [6]. In 2012, F. Lang, J. Yang, presented a new spectral-spatial classification method for hyperspectral images. First, statistical region merging (SRM) segmentation algorithm is extended to form a Hierarchical version, HSRM. The experimental results illustrate that the proposed method is able to generate more homogenous regions similar to MRF based methods [9] while preserving the class boundaries as precisely as segmentation based methods. The proposed work is an extension of the SRM algorithm to successfully classify the buildings in the satellite image. Texture analysis is performed after the segmentation of image using SRM. It is observed that the texture analysis on the segmented image provides a better classification of building pixels.

II. STATISTICAL REGION MERGING

Statistical Region Merging (SRM) is a graph based algorithm used for image segmentation. Fig. 1 represents the algorithm used to find the similarities between adjacent regions based on Merging Predicate and Merging Order. The regions in an image are merged based on a pre-defined Merging Threshold.

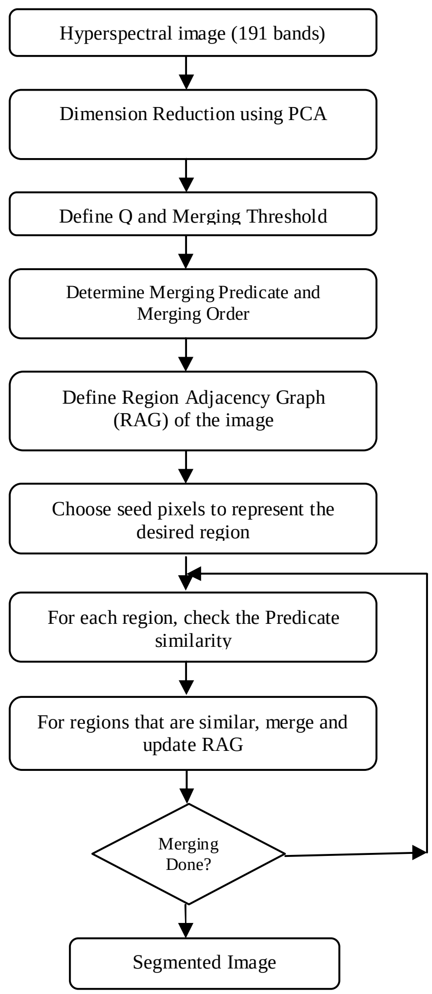

Figure 1. Flowchart Of SRM Segmentation Algorithm

III. TEXTURE ANALYSIS

Texture is a property that relates to the surface and structure of an image. Texture analysis is an important step in image segmentation and image shape identification tasks. This technique refers to a class of mathematical procedures and models that exemplify the spatial variations within images as a means of extracting information. Image segmentation is based on properties such as smoothness, coarseness and regularity that are used to quantify the texture of an object. The first order features include variance, average, entropy, skewness of each pixel in the image. Variance in the gray level in a region in the neighbourhood of a pixel is a measure of the texture [4].

$$T_v(x, y) = \frac{1}{n*n}\sum_{s=-n/2}^{n/2}\sum_{t=-n/2}^{n/2}|g(x+s, y+t)-\bar{g}|^2 \quad (1)$$

$$\bar{g} = \frac{1}{n*n}\sum_{s=-n/2}^{n/2}\sum_{t=-n/2}^{n/2}g(x+s, y+t) \quad (2)$$

Where, s and t are the positional differences in the x, y direction. (1) and (2) gives the variance of a pixel with respect to its neighbouring pixels. The difference in the variance values of pixels belonging to different classes is taken as a feature for classification.

IV. PROPOSED SYSTEM

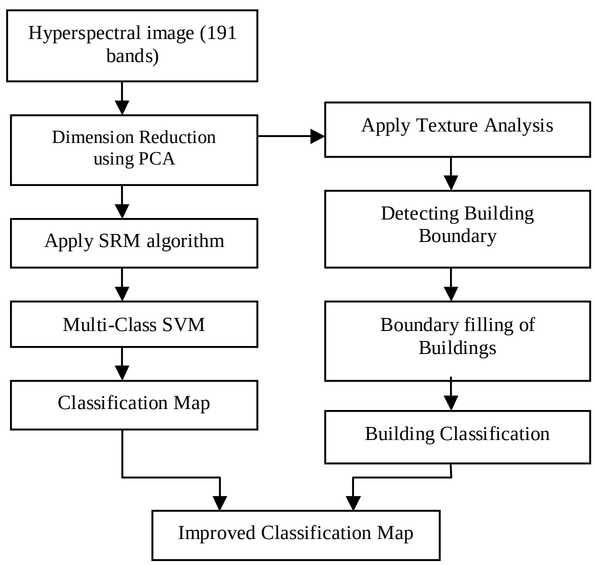

Figure 2. System schematic

Fig. 2 represents the basic flowchart of the proposed system. Hyperspectral image consisting of Hydice Washington DC of dimensions 306x306 consisting of 6 classes, namely, water, road, grass, trees, land and building is considered. Principal Component Analysis is performed to reduce the dimensionality of the image. Thus, at the end of this stage, the 191 band image is reduced to 3 principal components. After dimensionality reduction, segmented image consisting of different classes is obtained on the application of Statistical Region Merging algorithm. After segmentation, a multi-class Support Vector Machine (SVM) classifier [5] is implemented. The SVM algorithm consists of two phases:

Training Phase: Using the TrainData and Group matrices, the SVM is trained using Radial Basis Function (RBF) as the kernel and Euclidean distance as the measure.

Testing Phase: In this phase, the whole image is taken as the TestData and is given to the classifier. The class labels for each image data point are obtained. Once the classification map is obtained, texture analysis on the 3 component PCA image is performed. Boundary of the buildings is detected using Boundary Detection and filling algorithm.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Data

Fig. 3 shows the Hydice Washington DC hyperspectral image taken on August 1995, consisting of 191 bands is used for the implementation. Its ground sample distance is about 3.2 meters. Its flight height was about 6320m. The bands are in the 0.4 to 2.4 μm region of the visible and infrared spectrum. This data set contains 1208 scan lines with 307 pixels in each scan line [2]. 306 X 306 pixels in the image are considered for analysis.

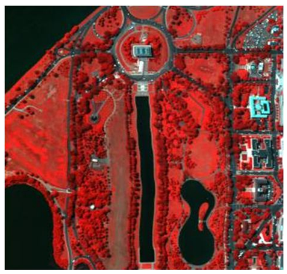

Figure 3. Hydice Washington DC Hyperspectral Image

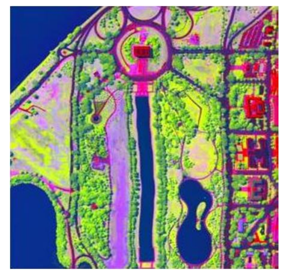

Figure 4. 3 Component PCA Image

Principal Component Analysis (PCA) is performed on this hyperspectral image and the output is as shown in Fig. 4.

TABLE 1. PERCENTAGE VARIANCE OF 3 COMPONENTS

Component Number	Percentage Variance (%)
1	73.61
2	19.78
3	5.13
Total Variance of 3 components	98.52

The percentage variance for each band is calculated and is tabulated as shown in Table 1 to understand and quantify the information contained in each of the 3 components separately. The total percentage variance for 3 components accounts to 98.52% which shows that the PCA image used contains almost 98% of the total information contained in 191 band images.

B. Ground Truth

Ground truth is generated using the rule files for each of the 6 classes. The spectral signatures for all the classes as shown in Fig. 5 are considered. The rule files of the individual classes as shown in Fig. 6 are a binary image which highlights the pixels of the classes.

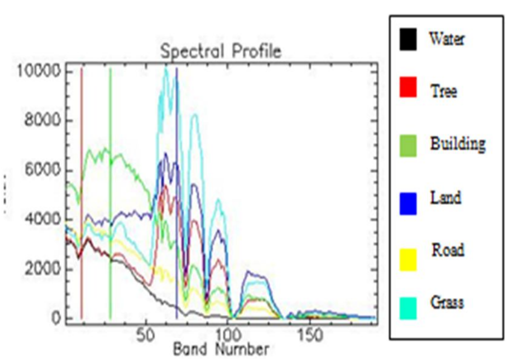

Figure 5. Spectral signatures of different classes

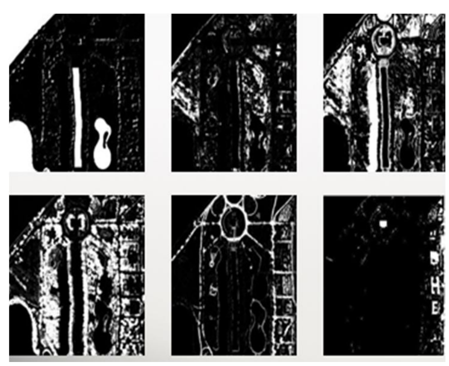

Figure .6 a to f Rule files for 6 classes

The rule files of all the classes are combined to form the ground truth represented by Fig. 7.

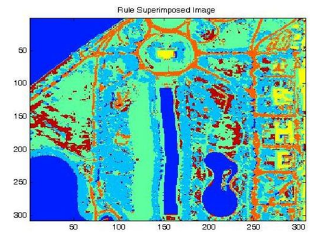

Figure 7. Ground Truth For Accuracy Analysis

C. SRM

The SRM segmented image as shown in Fig. 8 consists of segments of different intensity levels combined to form regions. Each region is assigned the average intensity value of that region. The segmented image is applied as input to the multi-class SVM.

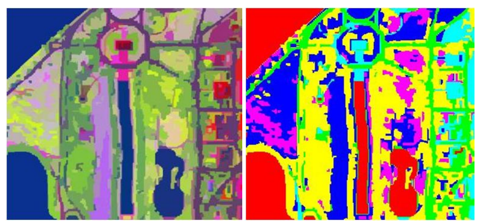

Figure 8. Srm Segmented Image And Srm-Svm Classified Image

The SRM-SVM classified image represented by Fig. 8 consists of 6 class labels.

D. Building Detection

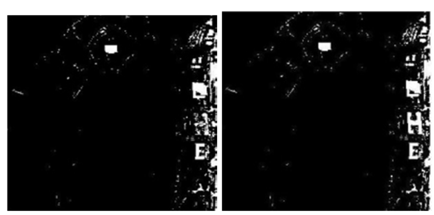

Figure 9. Building Before And After Boundary Filling

The accuracy of building classification is increased by implementing the boundary filling algorithm which can be observed in Fig. 9. This can be quantified by the confusion matrix for the supervised classification. Confusion matrix is used to test the classifier performance. The diagonal of the confusion matrix gives the correctly classified class pixels.

TABLE 2. CONFUSION MATRIX FOR SRM

SRM compared with Ground Truth						
Class	Water	Tree	Land	Building	Road	Grass
Water	**15615**	878	32	44	1037	4
Tree	104	**22689**	839	129	1154	1067
Land	129	2870	**17333**	2379	1743	1716
Building	19	831	193	**1612**	1480	152
Road	244	612	154	1802	**6442**	12
Grass	20	2513	1512	171	95	**5944**

TABLE 3. CONFUSION MATRIX FOR SRM-SVM

SRM- SVM compared with Ground Truth						
Class	Water	Tree	Land	Building	Road	Grass
Water	**15583**	357	12	23	583	1
Tree	61	**20480**	669	141	800	903
Land	20	1191	**14742**	736	792	849
Building	1	143	18	**1882**	508	8
Road	105	337	114	1117	**5099**	20
Grass	11	951	364	99	13	**3628**

Tables 2, 3 and 4 give the confusion matrix for SRM, SRM-SVM and SRM with texture analysis. The highlighted elements represent the correctly classified pixels.

TABLE 4. CONFUSION MATRIX FOR SRM WITH TEXTURE ANALYSIS

SRM after Texture Analysis						
Class	Water	Tree	Land	Building	Road	Grass
Water	**15536**	695	28	18	638	2
Tree	105	**21301**	940	138	702	1235
Land	241	5954	**18105**	3052	3643	2913
Building	2	138	38	**2128**	887	7
Road	137	752	214	1694	**6607**	58
Grass	111	1548	758	139	181	**4679**

TABLE 5. COMPARISON OF PERCENTAGE ACCURACY

Hydice Washington-DC Image			
Classes	Percentage Accuracy		
	SRM	SRM-SVM	SRM- Texture Analysis
Water	94.1059	91.8366	88.6712
Tree	88.8349	87.2241	87.3258
Land	66.2323	53.3945	80.4255
Building	**44.3056**	**63.7102**	**70.3930**
Road	70.0562	69.2912	72.0736
Grass	71.6147	57.9733	63.0933

Table 5 compares the percentage accuracy. As can be seen, the accuracy of building class is increased by the application of texture analysis.

VI. CONCLUSION AND FUTURE WORK

The paper presents a supervised classification technique using SVM. SRM segmentation algorithm is implemented on the Hydice DC image. Accuracy is compared using confusion matrices. The percentage accuracy of the building class is increased by 6.68% after texture analysis is implemented. The results indicate that the proposed method, by integrating the advantages of SRM and texture analysis techniques, can give high classification accuracy for the building. This is because both spatial and spectral analysis techniques have been integrated. Shape analysis can be implemented to further improve the classification accuracy of different classes.

REFERENCES

[1] Yuliya Tarabalka, Jocelyn Chanussot, Jon Atli Benediktsson, “Segmentation and classication of hyperspectral images using watershed transformation”, Pattern Recognition, Elsevier, 2010, 43 (7), pp.2367-2379.

[2] Bethel, J., Lee, C., Landgrebe, D., “Geometric Registration and Classification of Hyperspectral Airborne Pushbroom Data”, Proceedings of ISPRS 19th Congress, Amsterdam, The Netherlands, July 2000.

[3] Yuliya Tarabalka, Jocelyn Chanussot and Jo´n Atli Benediktsson, “Segmentation and Classification of Hyperspectral Images Using Minimum Spanning Forest Grown From Automatically Selected Markers”, IEEE Transactions On Systems, Man, And Cybernetics—Part B: Cybernetics, Vol. 40, No. 5, October 2010

[4] G. N. Srinivasan, And Shobha G., “Statistical Texture Analysis”, Proceedings Of World Academy Of Science, Engineering And Technology Volume 36 December 2008 Issn 2070-3740

[5] Farid Melgani, Lorenzo Bruzzone, “Classification of Hyperspectral Remote Sensing Images With Support Vector Machines”, IEEE Transactions On Geoscience And Remote Sensing, Vol. 42, No. 8, August 2004.

[6] Richard Nock, Frank Nielsen, “Statistical Region Merging”, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 26, No. 11, November 2004

[7] Yuliya Tarabalka, Jocelyn Chanussot, Jon Atli Benediktsson, Jesus Angulo, and Mathieu Fauvel, “Segmentation And Classification Of Hyperspectral Data Using Watershed”, IGARSS 2008.

[8] B. Krishna Mohan and Alok Porwal, “Hyperspectral image processing and analysis”, Current Science, Vol. 108, No. 5, 10 March 2015.

[9] Meysam Golipour, Hassan Ghassemian, and Fardin Mirzapour, “Integrating Hierarchical Segmentation Maps With MRF Prior for Classification of Hyperspectral Images in a Bayesian Framework” , IEEE Transactions on Geoscience and Remote Sensing, Volume: 54, Issue: 2, Feb. 2016

[10] Luis Ignacio Jim´enez, Victor Andr´es Ayma, Raul Queiroz , “Segmentation as Postprocessing for Hyperspectral Image Classification”, European Union IEEE 2015.