

Segment based classification of Indian urban environment

Virendra Pathak and Onkar Dikshit
Department of Civil Engineering
IIT-Kanpur, Kanpur-208016 (UP), India
e-mail: vireniet@hotmail.com, onkar@iitk.ac.in

Abstract- This paper presents results of segment based classification of an Indian urban environment. This approach to classification involved three stages. In the first stage, a region based multispectral segmentation of the image was carried out after determining suitable automatic threshold values considering textured nature of imagery. The second stage involved refinement of initially segmented image, iteratively by merging smaller segments with the most similar adjacent segments until they satisfied a homogeneity criterion. Finally, these segments were classified into 12 different classes using various spectral and textural properties of segments. Three different types of classifications were performed: the per-pixel Gaussian maximum likelihood classification (GMLC), the per-segment GML classification, and the per-segment neural classification. Result showed that the per-segment classification improves overall classification accuracy by more than 25% in comparison to the per-pixel approach.

I. INTRODUCTION

Inclusion of spatial information in the form of texture using the window-based approach has inherent drawback of choosing a suitable window size. Another way of including spatial information is by classifying the image on segment basis or per field basis also known as region based. The field base or region base is important because a region as a whole contains more information than its individual pixels, but also because region are atomic entities for structural and semantic analysis in middle and high level vision.

Image segmentation has been the subject of extensive research in the areas of computer vision and pictorial pattern recognition in the recent past. The objective of using segmentation algorithm in classification of urban environment is to cater for widely different textured images of urban environments. Natural scenes often contain feature gradients, highlights, shadows, texture and small objects with fine geometric structure, all of which make the process of producing useful segmentation difficult. This study presents investigation pertaining to the region-based approach of classification for a typical urban environment.

II. OBJECTIVES, STUDY SITE AND DATA RESOURCE

The objective of this study was to evaluate results of segment based classification in comparison to pixel based GMLC. Another objective was to investigate use of neural network in segment based classification and inclusion of texture information of segments in the classification process. The study area is a typical urban Indian city Lucknow, the state capital of northern Indian state Uttar Pradesh. The geographical extent of Lucknow ranges between North latitudes $26^{\circ} 45'$ and 27° and the East longitudes $80^{\circ} 50'$ and $81^{\circ} 5'$. A central extract (512x512 pixels) from the area is chosen for this study. Twelve classes covered the majority of urban land use features. The satellite data for the study area included three multispectral bands of IRS-1C, LISS-III sensor.

III. THEORITICAL BACKGROUND

The investigations in this paper have used three different thresholding methods, namely Johannsen and Bille, Otsu, Trussel [1-3]. After getting threshold values of multispectral bands, LISS-III multispectral image was segmented. This image was further refined by a region-merging approach proposed by Beveridge *et al.* [4] The approach calculates a merge-score. A merge-score less than one indicates a preference for merging, while values greater than one dictate against merging. It is possible to incorporate many segment attributes to determine the merger of segments.

Finally, for classification of segmented image into land use classes, the per-pixel and the per-segment GMLC was used. For Artificial neural network (ANN) classification, Resilient backpropagation method was used. Texture properties in the form of standard deviation (SD) and Grey level co-occurrence matrix (GLCM) texture feature *Mean* was used to provide information about the spatial distribution of spectral variations [5].

IV. EXPERIMENTAL METHODOLOGY

For finding threshold for a given spectral band, first a difference image using 3x3 operator was created. This differential image was operated upon by a moving window covering full image. Histogram for each position of moving window was prepared and threshold value for each position was calculated. Finally, the threshold value having highest frequency of occurrence for all positions of moving window was selected as global threshold value. Likewise threshold values for all bands were calculated.

Using thresholds obtained by using the aforementioned approach, the spectral bands were subjected to segmentation. The region-based approach has been implemented in the present work. The segmentation algorithm operates in two phases. In the first phase, initial segments were grown from randomly selected seed pixels after that the second phase started from the first pixel in the image by scanning from left to right and top to bottom. The second phase considered all those pixels that were not included in segments grown during the first phase.

The output of this process was a label image with a label number assigned to each segment. The label image obtained as a result of the initial segmentation was refined iteratively until criterion of merge-score was met. In the present investigation, a grand merge-score was calculated as a function of three properties: spectral value, size and connectivity.

In the final stage, these segments were classified using various spectral and textural properties of segments. Textural properties like standard deviation, GLCM texture feature *Mean* were used. Three different types of classifications were performed, the per-pixel GMLC, the per-segment GMLC and the per-segment neural classification. For all classifications, the overall classification accuracy and the accuracy of the individual classes were assessed by computing kappa coefficients (κ) and associated asymptotic variances. Pair-wise statistical tests were performed to assess the significance of any differences observed between two classifications using a Z statistic [6].

V. RESULTS

A. Thresholding and Segmentation

Out of the three methods implemented for finding threshold values, segmentation results using threshold values derived from Otsu method are visually better than other method used for the study. Threshold values for multispectral bands were found to be 13,11,10 respectively for band 1, 2 and 3. Segmentation of multispectral bands was carried out with respective threshold values.

B. Refinement of Segmented images

Once the initial segmented image was obtained, it was refined so that smaller segments were reduced by merging them to bigger segments. After 203 iterations of merging process, segments got stabilized.

C. Classification of Segmented images

The overall classification accuracy and the accuracy for most of the classes were significantly higher for segment based classification. Further, results of per-segment classification reveal that the per-segment neural classification provides slightly higher accuracy than per-segment GMLC. Use of GLCM texture feature *Mean* in the per-segment neural classification also provides higher, but statistically insignificantly different accuracy than the per-segment neural classification with pure spectral features.

VI. CONCLUSIONS

1. Otsu method of finding threshold provides better segmentation results compared to other two methods considered for the study.
2. The per-segment GMLC provides significantly higher test accuracy than the per-pixel GMLC.
3. The per-segment ANN classification provides slightly higher, though statistically insignificantly different, test accuracy than the per-segment GMLC.
4. Use of Standard Deviation values of segments as texture information reduces test accuracy in the per-segment ANN Classification.
5. Use of GLCM texture feature *Mean*, derived from spectral features improves test accuracy in the per-segment ANN Classification though it is statistically insignificantly different.

REFERENCES

- [1] G. Johannsen and J. Bille, "A threshold Selection method using Information measures", *Proceedings of the 6th International Conference on Pattern Recognition, Munich, Germany*, pp. 140-143, 1982.
- [2] N. Otsu, "A threshold selection method from grey-level histograms", *IEEE Trans. on systems, Man, and Cybernetics*, SMC-8, No.1, pp. 62-66, 1979.
- [3] H.J. Trussel, Comments on "Picture Thresholding Using an Iterative Selection Method", *IEEE Trans. on systems, Man, and Cybernetics*, SMC-9, No. 5, p. 311, 1979.
- [4] J.R. Beveridge, J. Griffith, R.R. Kohler, A.R. Hanson and E.M. Riseman, "Segmenting Images using localised histograms and region merging", *International Journal of Computer Vision*, vol. 2, pp. 311-347, 1989.
- [5] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural features for image classification", *IEEE Trans. on Systems, Man, and Cybernetics*, SMC-3, pp. 610-621, 1973.
- [6] R. G. Congalton, R.G. Oderwald and R.A. Mead, "Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Statistical Techniques", *Photogrammetric Engineering and Remote Sensing*, vol. 49, pp.1671-1678, 1983.