#### REGION EXTRACTION IN SPOT DATA

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#### ABSTRACT

This paper presents a method for segmenting SPOT HRV data using color edge points to separate small regions with nearly constant color. Region segmentation using edge points has not been successful because edge detection operators yield the partially enclosed regions. The present method uses isograms of equal distances from the boundary points between the partially enclosed regions. The small enclosed regions (primitive regions) are separated, based on the local isogram maxima and their values. After SPOT data have been segmented, spectral and spatial features such as color, vegetation index, size and shape are extracted for each primitive region. It is shown that the primitive regions corresponding to typical land cover types (rice field, urban area, residential area, forest, highway and river) are successfully characterized by spectral and spatial features.

### 1. INTRODUCTION

In the classification analysis of satellite multispectral sensor (MSS) data, the statistical methods based on multispectral classifiers have been extensively utilized. In the statistical classification methods, however, it is difficult to recognize complex surface features reliably. This is because the results of classification show only the pixels with similar multispectral properties. Spatial patterns that characterize the object are not taken into account.

The automated scene analysis systems for high resolution aerial photographs have been studied by several authors (Nagao, et al., 1979; McKeown, 1984; Harlow, et al., 1986; Hwang, et al., 1986). However, a detailed analysis of the satellite MSS data using artificial intelligence techniques was of little practical use, because the desired objects and structures were small compared to the pixel size of the satellite image. The resolution of SPOT HRV data is sufficient to require the advanced image processing system for the integration of spatial and multispectral analyses.

In this paper we describe the region extraction in SPOT HRV data (ID number : 0135638L), based on an edge-based segmentation technique. Region segmentation using edge points has not been successful. The prime cause is the presence of small gaps in edge boundaries which allow merging of dissimilar regions. The method described here uses isograms of equal distances from the boundary points between the regions that are partially enclosed by the thined edge points. Using the local isogram maxima and their values, we can easily separate the regions. The separated regions will be referred to as the primitive regions. After SPOT data have been segmented, spectral and spatial features such as color, vegetation index, variance of the brightness, size, shape and compactness are computed for each primitive region. Consequently, it is shown that the regions corresponding to typical land cover types (rice field, urban area, residential area, forest, play ground, highway and river) are successfully classified by using spectral and spatial features.

#### 2. EXTRACTION OF PRIMITIVE REGIONS

In order to extract the primitive regions with nearly uniform color from multispectral SPOT HRV data, we performed the following processes:

- 1) edge-finding operation,
- 2) thinning operation,
- 3) eliminating noisy edge points,
- 4) labelling primitive regions,

5) merging edge points into primitive regions.

Processes 1)-5) are applied to the 508x508 pixels area extracted from the fullscene of SPOT HRV data acquired on Aug. 20, 1986. The color composite image of SPOT data is shown in Fig.1 (a). The white regions in the central portion of the image represent the urban area or cloud. The brighter regions in the left hand side of the image represent agricultural land.

#### 2.1 Edge-finding operation

Color is the important feature for analysing the complex natural scene. We perceive that the color composite image of SPOT data yields many details about scene structure. Therefore, color edges are detected using three spectral bands of SPOT data. We assume that color edge magnitude is the linear combination of edge magnitudes detected from SPOT data in each band.

The edge magnitude G(i) in i-th band is calculated, using the Sobel operator approximated by the absolute-value operator. The color edge magnitude M is given by

$$M = (\tilde{\Sigma}_{i}G(i)/2) / 3$$
 (1)

Color edges are obtained by applying this operation to every pixel of SPOT data. Hereafter, the color edge magnitude will be simply referred to as the edge magnitude.

# 2.2 Thinnig operation

The edge points are thinned to produce sharp ridges. The thinning operation described here is based on the assumption that edges of low contrast usually do not correspond to real region discontinuities. First, we find a candidate for real edge points, based on the threshold selection algorithm that utilizes the histogram of the edge magnitude (Kohler, 1981). The threshold T is selected at the median value between the average edge magnitude and the edge magnitude corresponding to the highest peak in the histogram. Next, the edge data whose values are edge magnitudes are again scanned left-to-right,





- Fig.l (a) Original SPOT image, (b) Thinned edge image,
  - (c) Superimposition of Fig.(a) and (b),
  - (d) Final results obtained from the region extraction processing

top-to-bottom. If the edge magnitude D at a given point is greater than T, then two neighbors at that point are examined in vertical, horizontal, and two diagonal directions. If the value D at the currently considered point is greater than that of its two neighbors, that point is determined to be the real edge point. We have the thinned edge data whose values are 1 or 0 by applying the operation described above to the edge data.

# 2.3 Eliminating noisy edges

The thinned edge points involve the isolated edges (noisy edges) which consist of one or two edge points. To eliminate the noisy edges, we perform the following processes. 1) The thinned edge data are scanned left-to-right, top-to-bottom by applying a (2n+1)x(2n+1) pixel window at each point. If the edge point locates at the center of the window, then the edge points contained within the window are counted. If there are less than n+1 edge points, then the edge point locating at the center of the window is eliminated. In this operation, the end point of n+1 connected edge points is not eliminated.

2) Set n=n-1 and process 1) is iterated until n=1. In this study the initial value of n was set to 2. The result of eliminating noisy edges is shown in Fig.1 (b). Moreover, the thinned edge image was superimposed on the original SPOT image (see Fig.1 (c)). Fig.1 (c) greatly enhances the structual contrast. We can recognize small structures in SPOT image clearly.

2.4 Labelling primitive regions

The thinned edge points do not always give us the completly enclosed regions. We, therefore, necessitate such a region extraction method that the regions are correctly separated, despite small gaps in the edge points. To do that, Perkins (1980) has used the expansion-contraction technique. Harms, et al. (1986) have discussed region segmentation using Rosenfeld's distance-transform algorithm (Rosenfeld, 1976) for blood cell analysis. We also use the distance-transform algorithm, but the work described here differs from the work described in Harms' paper by the method separating regions.

The region extraction method described in this paper is as follows: 1) all edge points are set to 0 and others 1. 2) isograms of equal distances from the boundary points between the partially enclosed regions are constructed. 3) the local isogram maxima are found. They are regarded as the nuclei of the primitive regions. The same label is given to the four-connected pixels in each nucleus. 4) each nucleus is expanded with the aid of region growing technique. The pixels that will be adjacent to the regions already labelled are examined. If the pixel under consideration is either the pixel with value 0 or the pixel with different label, then the expansion is terminated. Otherwise, the expansion is performed.

Fig.2 Schematic diagram of the region extraction processing

Size (Number of pixels)	Number of primitive regions
$\begin{array}{c} 1\\ 1\\ 2\\ 3\\ 4\\ 5\\ 6\\ 7\\ 8\\ 9\\ 10\\ 11 \sim 20\\ 21 \sim 30\\ 31 \sim 40\\ 41 \sim 50\\ 51 \sim 100\\ 101 \sim 765\end{array}$	$\begin{array}{c} 2 \ 0 \ 9 \ 7 & (1 \ 7 \ 6 \ \%) \\ 1 \ 4 \ 8 \ 4 & (1 \ 2 \ 5 \ \%) \\ 1 \ 0 \ 2 \ 0 & (8 \ 6 \ \%) \\ 7 \ 4 \ 0 & (6 \ 2 \ \%) \\ 6 \ 0 \ 4 & (5 \ 1 \ \%) \\ 4 \ 9 \ 9 & (4 \ 2 \ \%) \\ 4 \ 5 \ 4 & (3 \ 8 \ \%) \\ 4 \ 0 \ 3 & (3 \ 4 \ \%) \\ 3 \ 6 \ 4 & (3 \ 1 \ \%) \\ 3 \ 6 \ 4 & (3 \ 1 \ \%) \\ 3 \ 2 \ 5 & (2 \ 7 \ \%) \\ 1 \ 8 \ 6 \ 3 & (1 \ 5 \ 6 \ \%) \\ 7 \ 9 \ 4 & (6 \ 7 \ \%) \\ 4 \ 3 \ 9 & (3 \ 7 \ \%) \\ 2 \ 0 \ 7 & (1 \ 7 \ \%) \\ 4 \ 3 \ 9 & (3 \ 7 \ \%) \\ 2 \ 0 \ 7 & (1 \ 7 \ \%) \\ 4 \ 2 \ 5 & (3 \ 6 \ \%) \\ 1 \ 9 \ 3 & (1 \ 6 \ \%) \end{array}$
L	Total number 1 1 9 1 1

Table 1 The size and the number of primitive regions

Table 2 The size and the number of primitive regions after merging edge points

Size (Number of pixels)	Number of primitiveregions
$ \begin{array}{c} 1\\ 2\\ 3\\ 4\\ 5\\ 6\\ 7\\ 8\\ 9\\ 10\\ 11 \sim 20\\ 21 \sim 30\\ 31 \sim 40\\ 41 \sim 50\\ 51 \sim 100\\ 101 \sim 795 \end{array} $	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
	Total number 1 2 2 7 8

The schematic diagram of processes 1)-4) is shown in Fig.2. In Table 1, the size and the number of primitive regions are shown. We can see from Table 1 that there are many small primitive regions. We also find that the number of edge points is about 1/3 times as many as that of all the pixels belonging to primitive regions. Therefore, edge points which touch two different regions must be assigned to either of two regions.

### 2.5 Merging edge points to primitive regions

In general, edge pixels are separated into two classes (active and inactive). Active edge pixels are defined as edge points which are not merged to any adjacent regions. On the other hand, inactive edge pixels are merged to the adjacent regions. Whether the edge pixel is active or inactive depends on the contrast between the edge pixel and its adjacent regions. Since we deal with color edge points, we define the color contrast L as follows:

$$L = \sum_{j=1}^{3} |I(j) - \overline{I}(j)|$$
 (2)

where I(j) and I(j) are the grey level of the edge pixel and the average grey level of the adjacent region in band j, respectively. For each primitive region that is adjacent to the edge pixel, color contrast L is computed. Then, the primitive region with the minimum contrast is identified. At that time, the threshold at the color contrast is set to 3xT. If minimum contrast is less than 3xT, the edge pixel is inactive and is merged to the region with the minimum contrast. Otherwise, the edge pixel is active. After all edge pixels have been scanned, active edge pixels are connected to form a new primitive region.

The size and the number of the primitive regions after merging edge pixels are summarized in Table 2. The final result obtained from our region extraction method is shown in Fig.1 (d).

# 3. CHARACTERISTIC PROPERTIES OF LAND COVER TYPES

We extract spectral and spatial properties of primitive regions to use them in classification of various land cover types. We chose the following attributes for each primitive region :

- a) average grey level in each spectral band (GL),
- b) normalized vegetation index (NVI),
- c) variance of the brightness (VB),
- d) area (A),
- e) maximum distance (D),
- f) form factor  $(A/D^{**2})$ ,
- g) compactness (C).

Since it is difficult to determine the color code of each region uniquely, we chose the average grey level in each band instead of color code. NVI is defined as (XS3-XS2)/(XS3+XS2), where XS3 and XS2 are average grey levels in band 3 and band 2, respectively. Property c) is considered to be a texture measure because VB provides the low value for homogeneous regions and the high value for highly textured regions. For simplicity, the brightness is defined as the value of the second component derived from the principal component analysis, because in our study site each component of eigen vector has positive value for the second principal component. A is the number of the pixels within the primitive region and D is the maximum value of isograms of equal distance in each primitive region. The form factor is nearly equal to unity for the circular region and increases for elongated shapes and irregular shapes. We also computed compactness defined as perimeter\*\*2/A.

The values of properties a)-g) are computed for the primitive regions corresponding to various land cover types. The categories of land cover types we used here are agricultural land (rice field), urban area, residential area I, residential area II, play ground, forest, highway, river and cloud. The residential area I and II are denoted as the thickly housed area and the dwellings interspersed in suburban area, respectively. About twenty primitive regions were extracted for each category by referring to the land use map at a scale of 1/25,000 and the average values of their spectral and spatial properties were computed. In Table 3, spectral features (properties a)-c)) are shown for each category of land cover types. Spatial features are shown in Table 4.

We find from Table 3 and 4 that large homogeneous regions such as rice field and forest are successfully characterized by spectral features. In particular, it should be noticed that the texture measure VB of forest significantly differs from that of rice field.

As seen from Table 3, the difference in the grey level in each band between residential area I and II is small. This indicates that in applying statistical methods using multispectral classifiers to SPOT data, two cover types for residential area are not distinguishable. Using NVI and spatial features, we can easily classify the regions corresponding to residential area I and II.

The regions representing urban area are characterized by spatial features such as form factor and texture measure VB. In other words, The form factor and VB give us relatively large values. Terefore, urban area is identified as the irregularly shaped and highly textured regions with the low value of NVI. River shows very prominent spatial characteristics as might have been expected. The value of form factor is very large. However, for the regions corresponding to highway, the form factor provides not so large value. This is because in our region extraction algorithm uniform regions are taken to be four-connected. We can not correctly extract the thin, obliquely elongated regions. Such regions will be extracted by using 8-connectivity algorithm.

We also find from Table 3 and 4 that the regions representing cloud and play ground are easily extracted by using spectral and spatial features.

# 4. CONCLUSIONS

Region segmentation method using the edge-based technique was applied to SPOT HRV data. The present method yields fairly good segmentation results in spite of small gaps in edge points. We also extracted spectral and spatial features of the segmented regions corresponding to typical land cover types. Consequently, we found that the form factor and texture measure

Category	Average v Band 1	values of Band 2	gray level Band 3	ΝΥΙ	Variance of brightness(VB)
Urban area	67.0	51.3	53.5	0. 023	87.0
Residential area I	58.8	43. 7	53.9	0.106	35.7
Residential area II	54.8	37.5	59.9	0.227	18.8
Rice field	54.0	34.3	93. 2	0.463	7.1
Forest	43.2	25.3	74.8	0.496	35.7
Play ground	90. 2	85.5	88.6	0.025	322. 5
Highway	57.8	39.7	70.5	0.258	8.4
River	50.8	33. 8	36.8	0.029	41.2
Cloud	147. 3	119.6	109.5	-0. 038	1096.1

Table 3 Spectral features for nine typical land cover types

Table 4 Spatial features for nine typical land cover types

Category	Area (A)	Maximum distance (D)	Form factor (A/D**2)	Compactness (C)
Urban area	43. 2	1.9	11.6	35.8
Residential area I	73. 0	3.5	7.2	36.2
Residential area II	37. 7	2.3	8.8	27.6
Rice field	179.1	7.6	3. 7	31.6
Forest	116.0	5.9	4.4	31.9
Play ground	25. 9	1.9	7.7	21.5
Highway	35. 2	2.1	8.8	31.3
River	46. 3	1.2	34.1	46.8
Cloud	24. 3	1.9	7.8	30. 1

VB (variance of the brightness) used here are important features to classify the regions with almost same spectral patterns.

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