AUTOMATIC IMAGE SEGMENTATION OF HIGH RESOLUTION REMOTE SENSING DATA BY COMBINING REGION AND EDGE INFORMATION

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ABSTRACT Image segmentation techniques becoming increasingly important in the field of remote sensing image analysis in areas such as object oriented image classification. This paper presents a new method for image segmentation in High Resolution Remote Sensing Image based on Seeded Region Growing (SRG) and Edge Information. Firstly, multi-spectral edge detection was done using an entropy operator in pan-sharpened QuickBird imagery. Then, the initial seeds were automatically selected from the obtained edge map. After automatic selection of significant seeds, an initial segmentation was achieved by applying SRG. Finally the region merging process, using region adjacency graph (RAG), was carried out to get the final segmentation result. Experimental results demonstrated that the proposed method has good potential for application in the segmentation of high resolution satellite images.

KEY WORDS: Seeded Region Growing, Region Merging, High Resolution Satellite Image, QuickBird.

1. INTRODUCTION

With the advent of high resolution imagery, the need for technologies that will enable urban monitoring and classification systems is rapidly growing. Automated land cover classification is very important for many urban applications such as road network and building footprint identification. The conventional methods, which only utilize spectral information such as maximum likelihood, make it difficult to obtain satisfactory results, because of the complex nature and diverse composition of land cover types found within the urban environment. To deal with this problem, region-based alternative approaches to meet the need for the object-oriented classification have recently been proposed. In such circumstances, the study of automatic image segmentation algorithms is significant because the quality of object-based classification is directly affected by segmentation quality. A variety of segmentation algorithms have been applied to remote sensing imagery with varying degrees of success (Evans, 2002). Segmentation of remotely sensed images is a difficult task due to mixed pixels, spectral similarity, and the textured appearance of many land cover types. Many segmentation algorithms are built on a region-growing approach where pixels are iteratively grouped into regions, based on predefined similarity criteria (Tilton, 1998, Jenson, 1996). A segmentation method for high-resolution satellite imagery using watershed transform combined with the region merging approach was proposed by Chen (2006) and Wang (2004).

In this paper, we apply SRG to multispectral images with automatic seed selection. Our proposed algorithm consists of three steps: In the first step, we automatically extract point seeds from a multi-spectral edge map, obtained from the entropy operator. In the second step, an initial segmentation is achieved by applying SRG based on a priority queue data structure. In the third step, the region merging process is used to get the final segmentation result. The entire workflow is illustrated in Figure. 1.

Multi-Spectral Edge Extraction with Entropy Operator

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Perform Automatic Seed Selection

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Initial Segmentation by Seeded Region Growing(SRG)

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Final Segmentation by Region Merging Process

Figure 1. Flowchart

2. MULTI-SPECTRAL EDGE EXTRACTION

We chose a fast, simple edge operator for identifying the geometric structures of an image. The detected edge results can then be improved by integrating them with the SRG procedure. The obtained edge information can provide a simplified image that preserves the domain geometric structures and spatial relationships found in the original image. This edge information is very useful for providing the structural seeds of an image. In this paper, we applied an entropy operator proposed by Shiozaki (1986) to a multispectral image for extracting the edge. The entropy operator is a nonlinear filter and rotation invariant. It calculates the entropy of brightness in the central pixel of the window mask. The entropy measure which provides information for the homogeneity of the region is defined as follows:

$$H = \sum_{i=0}^{n} p_i \log p_i / \log(n+1)$$

$$p_i = a_i / \sum_{j=0}^{n} a_j$$

where, a_i represents n neighbouring pixels and p_i is its probability.

The entropy operator in the n-dimensional spectral feature space can be expressed as a linear combination of individual entropy measures.

$$H = \sum_{i=0}^{n} q_i H_i \ , \ q_i = b_i / \sum_{i=0}^{n} b_i$$

where, $b_i = (b_{i1}, b_{i2}, \cdots, b_{1n})$ and H_i indicate pixel value and entropy measure of the central pixel in the local window. The entropy of a multi-spectral image takes high values in the edge region and low values in the flat regions.

3. THE PROPOSED SEGMENTATION ALGORITHM

In this section, our proposed segmentation algorithm is presented, which consists of a method comprised of automatic seed selection, seeded region growing and region merging. Details of the process are shown below.

3.1 Automatic Seed Selection

Region growing algorithms start form initial seed points and try to aggregate the yet unlabelled pixels to one of the given seed regions. The most critical part of the algorithm turns out to be the selection of the seeds. As the growing does not change the number of regions, a region lost during seed selection can not be recovered later. However, the conventional region growing algorithm chooses them randomly or by using a set priori direction of the image scan. In order to take a more reasonable decision, edge information can be used to decide the best position to place the seed. In this research, the seeds are homogenous pixels of the input multispectral space and multi-spectra edge map and are extracted when their homogeneity levels are greater than a predefined threshold. We can calculate the homogeneity level of a pixel by its standard deviation of the subimage covered by the rectangular regions with fixed size. The standard deviation of each component of the centre of these rectangular regions can be obtained by

$$\sigma_x = \sqrt{\frac{1}{n} \sum_{j=0}^{n} (x_i - \bar{x})}$$

where, x and $\bar{x}$ indicate pixel value of each component of multispectral bands and the mean value in the fixed rectangular area. The normalized total standard deviation can be expressed as

$$\sigma_N = \frac{\sigma_{total}}{\sigma_{\max}} \ , \sigma_{total} = \sum_{j=0}^{n} \sigma_j$$

where, $\sigma_{\max}$ is the maximum of the standard deviation in the multispectral image. When σ_N are large, the central pixel of a rectangular region could be defined as a non-homogenous pixel. Therefore, the homogeneity level of the multispectral image and the edge map is defined as

$$H_I = 1 - \sigma_{NI} \ , \ H_E = 1 - \sigma_{NE}$$

When the value of H_I and H_E for the central pixel of the rectangular region is greater than the specified threshold, it is selected to a seed which will be used in the SRG algorithm. We selected the threshold value of 0.8, based on our experiments.

3.2 Seeded Region Growing

Seeded region growing proposed by Adams and Bischof (1994) is a new approach which is based on conventional hypothesis region growing algorithms where the similarity criteria of pixels is applied, but the mechanism of growing regions is closed to the watershed algorithm.

Given the set of seeds, $S_1, S_2, \cdots, S_n$, each step of SRG involves one additional pixel to one of the seed sets. Moreover, theses initial seeds are further replaced by the centroids of these generated homogenous regions, $R_1, R_2, \cdots, R_n$, by involving the additional pixels step by step. The pixels in the same regions are labelled by the same symbol and the pixels in variant regions are labelled by different symbols. Let H be the set of all unallocated pixels which are adjacent to at least one of the labelled regions.

$$H = \left\{ (x,y) \notin \bigcup_{i=1}^{n} R_i \middle| N(x,y) \cap \bigcup_{i=1}^{n} R_i \neq \Phi \right\}$$

where $N(x,y)$ is the nearest eight neighbours of the pixel. Each step in the algorithm takes one pixel from H set and adds it to one of the regions with which neighbours $N(x,y)$ of the pixel intersect, actually labelling it with the label of that region. Then we examine all pixels form $N(x,y)$ and calculate the distance from their neighbouring regions. According to that distance, we put them into H set in increasing order. The distance is a simple measure which says how far the intensity of the regarded pixel is from the intensity mean value of those regions. It is defined as

$$\varphi(x,y)=\left|g(x,y)-\underset{(x,y)\in R_i}{mean}[g(x,y)]\right|$$

where $g(x,y)$ indicates the values of the each components of the testing pixel (x,y).

If $N(x,y)$ meets two or more of the labelled regions, $\varphi(x,y)$ takes a value of i such that $N(x,y)$ meets R_i and $\varphi(x,y)$ is minimized.

$$\varphi(x,y)=\min_{(x,y)\in H}\{\varphi(x,y,R_j)| j\in\{1,2,\cdots,n\}\}$$

The seeded region growing procedure is repeated until all pixels in the image have been allocated to the corresponding regions. The implementation of SRG employs a linked list sorting the data of H, which is put in order according to the $\varphi(x,y)$. Previous authors refer to this as the sequentially sorted list (SSL). In this paper, we make use of a data structure based on priority queue instead of SSL. The algorithm procedure for implementing this structure is as follow:

1) Find the initial set of candidate pixels, calculate their $\varphi(x,y)$ and put them into the priority queue.
2) While(Queue is not empty)
   a. Get the candidate pixel with the best $\varphi(x,y)$ from the queue.
   b. if(Candidate has more than one neighbouring regions) then
      Mark the pixel as the border region.
      Else
      Mark the pixel with the label of its neighbour region.
      Identify new candidates among the neighbours of the pixel just processed, calculate their $\varphi(x,y)$ and put them into the queue.

Figure 2. The implementation of SRG

Generally, the SRG algorithm produces a large amount of small regions as shown in Figure 5, which can be resolved by a region merging algorithm, described in the next section.

3.3 Region Merging Process

To further improve the initial segmentation result, we use an iterative region merging process that uses a region adjacency graph (RAG) data structure to represent the image partitions. In this process the most similar pair of adjacent regions is sequentially merged according to a predefined similarity metric. The RAG is defined as an undirected graph $G=(V,E)$, where V (*nodes*) represents regions of pixels and E (*edges*) indicates a neighbouring relationship. We assign *edge weights* to the edges to represent similarity between adjoining regions.

At each merging step, we require that the most similar adjacency region pair is to be merged. The RAG information is updated along with the neighbouring relations if the regions merged. There are several approaches to calculate the similarity of two regions. In this research, the region merging procedure is performed on the adjacent regions according to the Euclidean Distance of their mean vector.

This process will be terminated when the total region number is less than a predefined threshold. We defined the threshold value as 200, based on our experiment.

4. EXPERIMENTS AND DISCUSSION

In order to estimate the performance of the proposed image segmentation method, QuickBird high-resolution satellite image datasets, acquired on 25 May 2006, were selected. The site was located in Daejeon, Korea, which included various land-cover types such as those in Figure 4. High resolution QuickBird satellite images consist of one panchromatic (PAN) and four multispectral (MS) bands. The PAN data were fused with the MS data using PCI Geomatics' PANSHARP technique, which was developed by Dr. Zhang to generate a four-band pan-sharpened multispectral (PS-MS) image with 0.7m resolution (Zhang. Y., 2002).

Figures 3 and 4 show the multi-spectra edge map and the result of the automatic point seed selection.

Because of the high resolution character of the test image, the boundary of segments can be superimposed on the original image for visual inspection as shown Figures 5 and 6.

An initial segmentation based on SRG is shown in Figure 5; 1469 segments were obtained. It also shows obvious over-segmentation in local parts. After the proposed merging process, the final segmentation results with 113 segments were obtained, as shown in Figure 6. It is apparent that the over-segmentation has been improved. From Figure 6, we can see that the road and building patches were segmented quite well. However, the boundary of some buildings was not correctly represented due to spectral heterogeneity. In order to overcome this problem, it is necessary to further study region merging criteria and combining edge information.

5. CONCLUSION

In this paper, we proposed a new method of automatic image segmentation through combining edge and region information with QuickBird high-resolution satellite image datasets. The multi-spectral edges were first obtained by entropy operator and the initial seeds were automatically generated from an extracted edge map to provide more accurate segmentation result. Then an SRG algorithm was applied to the image to get an initial segmentation. At the final step, we applied a region merging process base on RAG to overcome the over-segmentation problem.

The experiments showed that our proposed method was rather promising but there were some problems in building patches. Our future research will focus on further testing of the proposed method in a variety of sites, and ways handle the limitations in the algorithm to improve segmentation accuracy.

Figure 3. Result of multi-spectral edge extraction

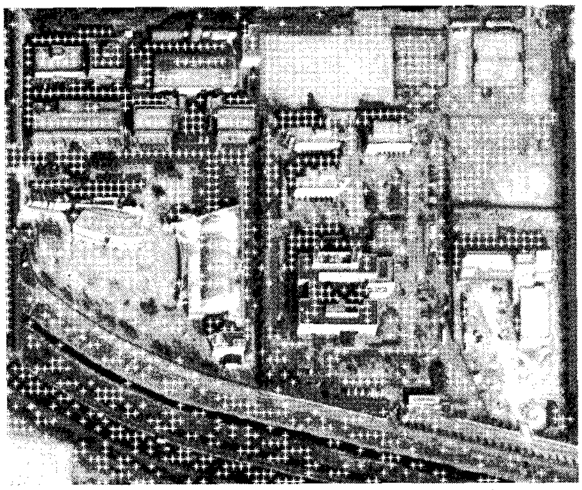

Figure 4. Result of automatic point seed selection

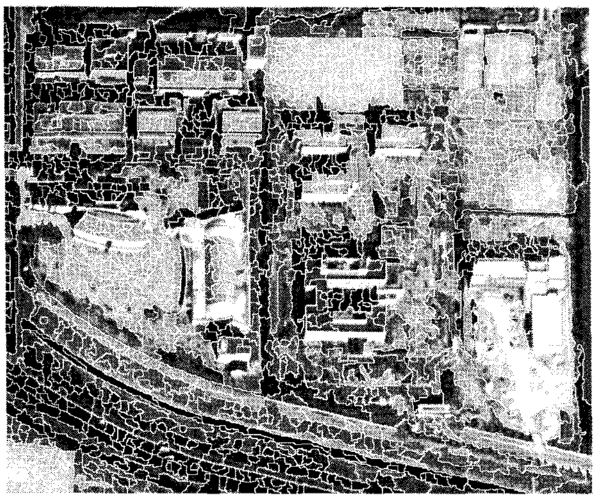

Figure 5. Result of initial segmentation

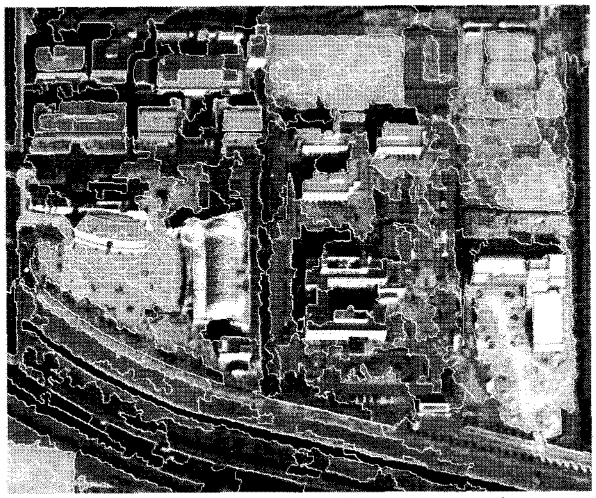

Figure 6. Result of final segmentation

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