A MULTI-SCALE REGION GROWING SEGMENTATION FOR HIGH RESOLUTION REMOTELY SENSED IMAGES

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ABSTRACT: For remotely sensed images, region growing segmentation is a widely-used technique for object extraction and identification. However, the main drawback of region growing segmentation is the threshold setting for stopping the growth of a region. Improper threshold setting not only causes over-segmentation or under-segmentation, but also cannot create needed object regions for various targets. In order to overcome these drawbacks, a multi-scale region growing segmentation method, based on the maximization of the change of edge density, is proposed. Experiments, including different kinds of high resolution remotely sensed images are used to test the performance of the proposed scheme. The experimental results show that the proposed scheme can both remove the limitation of threshold setting and generate relatively reasonable segmentation output for different types of objects.

1. INTRODUCTION

Due to the recent progress of remotely imaging systems, the image resolution of commercial sensors can reach to less than 1 m. Such high spatial resolution images definitely will provide a wealth of information for detail-thirsty users. Nevertheless, complex image content will make it difficult to develop image algorithms for automated image feature extraction and pattern recognition. Image segmentation is one of the useful techniques to extract regions' information from high resolution remotely sensed images. It is usually regarded as a preprocessing procedure for image classification (Black, 1998). One of a host of segmentation techniques, the region growing segmentation algorithm is an intuitive technique for extracting region features from images (Adams and Bischof, 1994). However, a problem with this algorithm is that the needed threshold setting for stopping the growth of a region is implicit to the general user. For example, improper threshold setting may cause over-segmentation or under-segmentation. Another difficulty is that the various region objects usually cannot be successfully segmented from a single threshold. Generally speaking, brighter targets, such as buildings or bare soil, can be partitioned with a higher threshold, but darker targets, such as roads or wetlands, usually need a lower threshold in region growing .

The main reason for these weaknesses is that the region growing algorithm is purely a region-based approach. This means that only region homogeneity is taken into account to delineate the region boundary during segmentation. In the literature, many modified region-growing methods have been designed to overcome the drawbacks mentioned above. These include better measures to describe the region homogeneity (Hojjatoleslami and Kittler, 1998), a gradient of source images used for growing regions(Meyer, 2001; Chen et al., 2006) and a tree-like graph that is created to search an optimized segmentation (Sanfeliu et al., 2002; Felzenszwalb and Huttenlocher, 2004).

In fact, given the complexity of high resolution remotely sensed images, multiple segmentation strategies should be integrated to solve the difficulties (Schiewe, 2002). In this study, a multi-scale region growing segmentation technique is proposed to cope with these problems. This study considers not only region homogeneity, but also includes the edge information of different scales to improve the segmentation result.

2. METHODOLOGY

Theoretically, each object has its own image homogeneity and can be grown in a single region using a certain threshold setting. However, if the threshold setting is smaller or larger than this certain value, the object will be over- or under-segmented. This explains why objects with different homogeneity always appear in the region growing outputs with different thresholds. In order to quantitatively describe this phenomenon for a partitioned object, the equation (1) for the edge density and equation (2) for the change of edge density are defined as follows:

$$\rho = \frac{E}{L} \qquad (1)$$

$$\rho' = \frac{d\rho}{ds} \qquad (2)$$

Where
ρ : Edge density
ρ' : Change of edge density
E : Total edge intensity
L : Edge length
s : Segmentation scale

Here the total edge intensity (E) is the sum of edge intensity over all edge pixels of the object. The edge intensity signifies the strength of the edge that is calculated by the Sobel gradient (Gonzales, 2002), and the edge length (L) is the number of all edge pixels of the object. Therefore, the edge density (ρ) means the edge intensity per unit length of the object. When a source image is partitioned using a region growing algorithm, different levels of threshold normally will produce segmentation results varying from fine to coarse details. This study will use the term segmentation scale (s) to refer to the different levels of threshold. In general, a smaller segmentation scale will produce more detailed segmentation results. As a result, the image will be gradually segmented from “over” to “under” stages. The detailed behavior of the edge density varies along the segmentation scale from fine to coarse, can be described as follows.

If an object is significantly over-segmented, the intensity of its boundary should be small and the shape is fragmented. It means that the edge density of the object is small. Nonetheless, when the segmentation scale increases gradually, the partitioned object should be less over-segmented and have greater edge density, due to the partition being closer to the observed target. This implies that the curve of edge density should be monotonic, increasing along with the segmentation scale. However, when the partitioned object is approaching the perfect partition, the edge density should have an abrupt change, because the shape of the partitioned object can nearly fit the observed target. The reason for this abrupt change is that the edge strength of the observed target is always locally the greatest. Then, if the segmentation scale continues to increase, the edge density will keep growing, but with a more moderate rate, while the partitioned object becomes under-segmented. In this study, the variation of the edge density is defined by the change of edge density (ρ'), which denotes the derivative of edge density with respect to the segmentation scale. Figure 1 illustrates the characteristic of edge density and the concept of perfect partition.

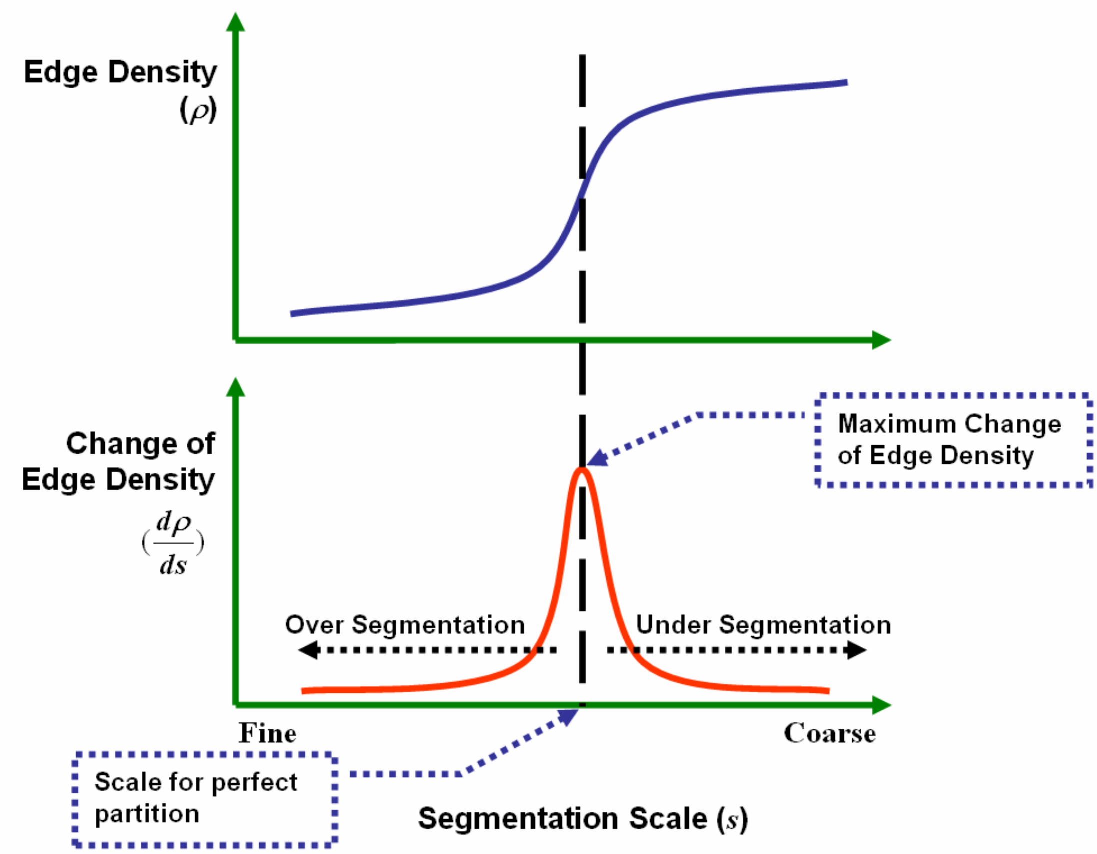

Figure 1. Characteristics of edge density and the concept of "perfect segmentation".

According to the above discussion, the perfect partition of an observed target should appear when the change of edge density of a partitioned object is maximum. In this study, a tree structure representing all scales of segmentation results has been created to search for this perfect partition.

The creating of the tree structure is described as follows. At the beginning, the region growing algorithm is applied with the smallest threshold to generate the finest scale of segmentation and tree nodes. Then, based on the previously generated segmentation, the region growing algorithm is applied again, with a larger threshold, to generate a coarser scale of segmentation and tree nodes. Finally, the whole procedure is completed when the largest threshold is reached. Notice that during the creation of each node, the total edge intensity and the edge length corresponding to the segment of the node are saved. After the creation of the tree, a searching procedure for finding the node of maximum change of edge density is followed. Figure 2 shows the searching procedure. Starting from the leaf node at the bottom of the tree structure, the change in edge density of each node is evaluated by comparing the edge densities between the parent node and the current node. Then, along the search path, changes of edge density of each node are compared. Finally, the internal nodes of maximum change of edge density for each leaf node can be found and a minimum spanning tree (Zahn, 1971), according to which these internal nodes can be determined. Figure 3 shows the determined minimum spanning trees for the entire image by the proposed method.

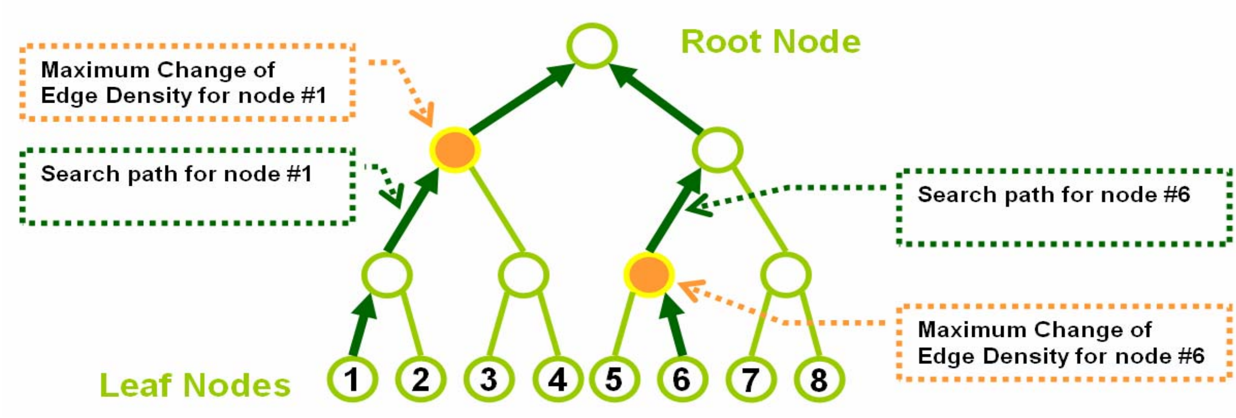

Figure 2. Searching procedure for finding nodes of maximum edge density.

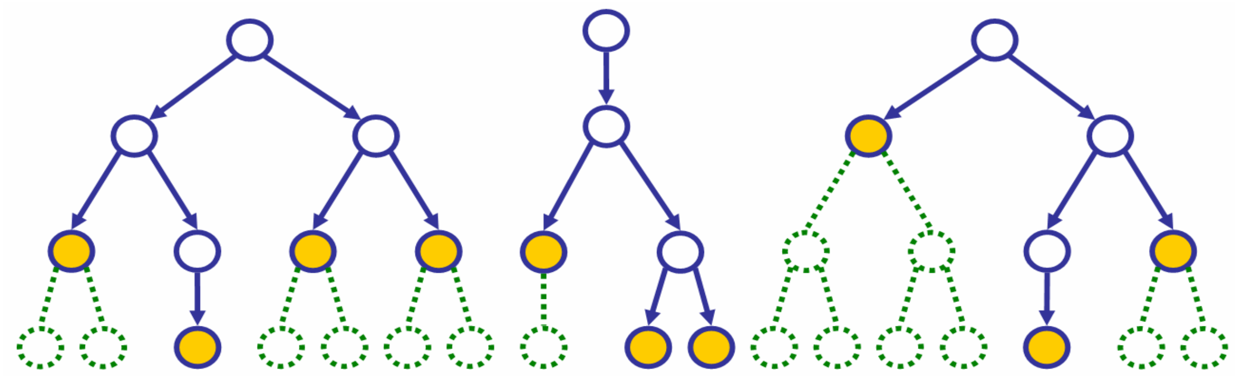

Figure 3. Minimum spanning trees for the entire image by the proposed method (connected by dark blue nodes and branches).

As soon as the minimum spanning trees are obtained, the image pixels represented by each leaf node of the minimum spanning trees can be identified as an image segment. Figure 4 illustrates the flow chart of the proposed scheme.

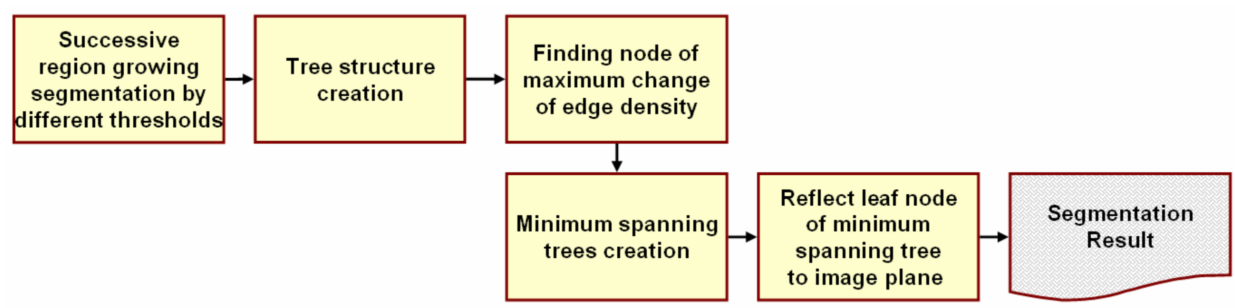

Figure 4. Flow chart of the proposed scheme.

3. EXPERIMENTAL RESULT

In this study, two kinds of images from different sensors are used to test the proposed algorithm. In the first and second case, images are acquired from earth resources satellites IKONOS. Image. In order to fully apply the information provided by the satellite sensor, the panchromatic mode and multispectral mode of the images are fused in advance. The technique used for image fusion is the high pass filter fusion method (Chaves, 1991 and Pohl, 1998). The second case uses the image acquired from an airborne digital camera. The most important feature of the sensor is that the image resolution of this camera is much higher than that of a satellite.

Case 1: IKONOS Satellite Image

In this case, a fused IKONOS satellite image is used to test the proposed scheme. The resolution of the image is 1 m. This area consists mainly of farmland and a number of buildings distributed along a main street. The source image used in this case is shown in figure 5(a). The segmentation result generated by the proposed scheme is shown in figure 5(b). To demonstrate the improvement brought about by the proposed scheme, segmentation results generated by the conventional region growing method, with different thresholds, are shown in figure 5(c) and (d). It can be observed that the proposed scheme can produce a reasonable segmentation without setting a threshold. Compared to the conventional region growing method, over- or under-segmentation results when different thresholds are applied.

Case 2: Image of airborne digital camera

In this case, an image of an airborne digital camera (UltraCam *D* by Vexcel) is used to test the proposed scheme. The resolution of the image is 0.2 m. This image comprises a part of the community and the shapes of house roofs can be distinguished. Further, the trees and lawns may be the most heterogeneous objects in this image. The source image used in this case is shown in figure 6(a). The segmentation result generated by the proposed scheme is shown in figure 6(b). The segmentation results generated by the conventional region growing method with different thresholds are shown in figure 6(c) and (d). It can be seen that reasonable segmentation without setting a threshold is generated by the proposed scheme, as well.

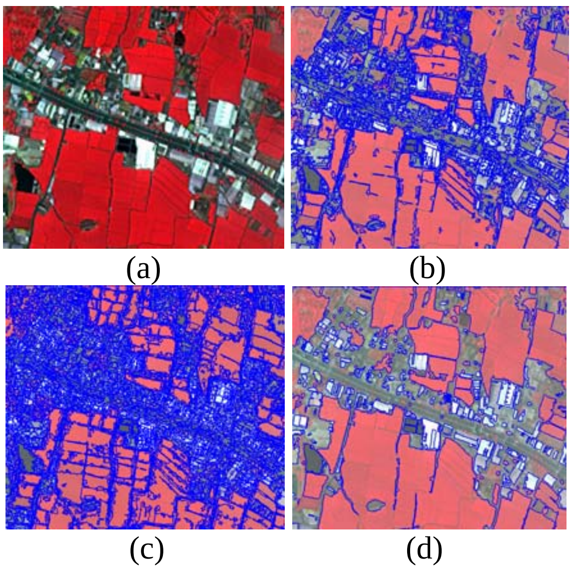

Figure 5. (a) the fused IKONOS satellite image. (b) the segmented result with proposed scheme. (c) the over-segmented result from region growing with a smaller threshold. (d) the under- segmented result from region growing with a larger threshold.

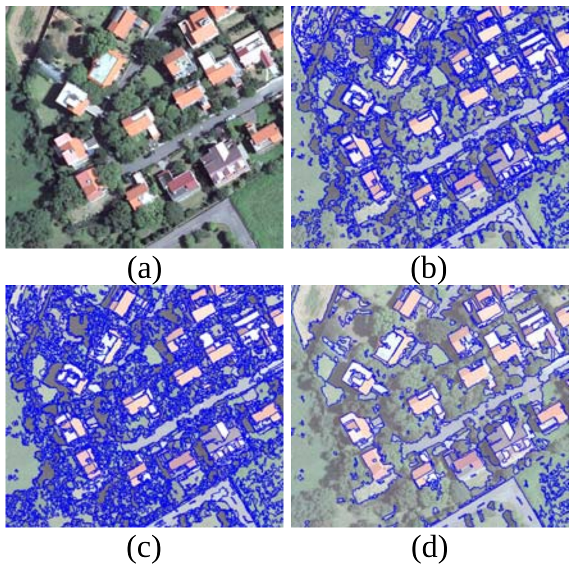

Figure 6. (a) the image from the airborne digital camera. (b) the segmented result with the proposed scheme. (c) the over-segmented result from region growing with a smaller threshold. (d) the under-segmented result from region growing with a larger threshold.

4. CONCLUSION

In this study, a multi-scale region growing segmentation technique is proposed as an improvement over the conventional approach. The core concept of the proposed method is to consider the edge information of different scales in order to acquire a more representative result.

With the proposed method, general users do not have to worry about the unknown threshold before segmentation. The experimental results show that the most important objects can be successfully partitioned. This result may provide suitable information for image classification and object identification in the next stage. However, some objects, such as buildings in satellite images, are slightly over-segmented by the proposed method. This problem may have occurred because the information used for region growing is only the spectral variation. In the future, more attributes, such as texture and semantic information, should be considered in the region growing process, in order to improve the final result.

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