HIGH RESOLUTION REMOTE SENSING IMAGE SEGMENTATION BASED ON GRAPH THEORY AND FRACTAL NET EVOLUTION APPROACH

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ABSTRACT:

Image segmentation is the foundation of further object-oriented image analysis, understanding and recognition. It is one of the key technologies in high resolution remote sensing applications. In this paper, a new fast image segmentation algorithm for high resolution remote sensing imagery is proposed, which is based on graph theory and fractal net evolution approach (FNEA). Firstly, an image is modelled as a weighted undirected graph, where nodes correspond to pixels, and edges connect adjacent pixels. An initial object layer can be obtained efficiently from graph-based segmentation, which runs in time nearly linear in the number of image pixels. Then FNEA starts with the initial object layer and a pairwise merge of its neighbour object with the aim to minimize the resulting summed heterogeneity. Furthermore, according to the character of different features in high resolution remote sensing image, three different merging criterions for image objects based on spectral and spatial information are adopted. Finally, compared with the commercial remote sensing software eCognition, the experimental results demonstrate that the efficiency of the algorithm has significantly improved, and the result can maintain good feature boundaries.

1. INTRODUCTION

With the development of remote sensing technology and the improvement of satellite spatial resolution, high resolution remote sensing images are widely used in various fields. High resolution remote sensing images have clear details and rich spatial and texture information. In order to take full advantage of this information, we started paying attention to the object-oriented image analysis.

Object-oriented image analysis starts with the crucial initial step of grouping neighbouring pixels into meaningful areas, which can be handled by image segmentation. Generally image segmentation is defined as a process of splitting an image into regions based on some criteria (intensity, colour, texture, orientation energy). The goal of image segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analysis. The quality of segmentation result greatly impacts the precision of the following analysis, such as classification, understanding and recognition.

For the past decade, many scholars and institutions have begun research on image segmentation and form a series of sophisticated algorithm and techniques. High resolution remote sening image segmentation, which is different from traditional image segmentation, contains many objects of different size, but most segmentation algorithm specify a spatial sclae at the object. We should be able to describe objects in a hierarchical scale, as a result we apply the mutil-scale image segmentaiton.

2. FRACTAL NET EVOLUTION APPROACH

Fractal net evolution approach (FNEA), as a widely used multi-scale segmentation algorithm, was first introduced by Baatz and Sch äpe (2000), and played an important role in the commercial software eCognition. This algorithm quickly became one of the most important segmentation algorithms within the object-oriented image analysis domain.

The basic idea of the algorithm is a bottom-up region merging technique. It starts with each image pixel as a separate object. Subsequently, pairs of image objects are merged into large objects at each step (Figure 1). The process terminates when no pair of objects satisfies the merging criterion. We will talk about the merging criterion later.

FNEA rely a key control, called the scale parameter, which controls the internal heterogeneity of the image objects and is therefore correlated with their average size, i.e., a larger value of the scale parameter allows a higher internal heterogeneity, which increases the number of pixels per image object.

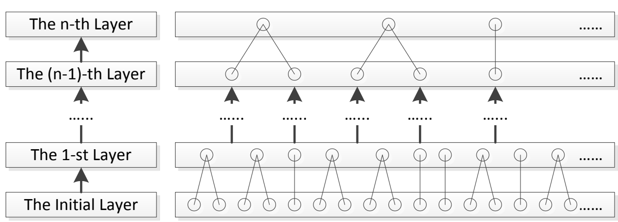


Figure 1. The object merging process of FNEA

However, the origial algorithm starts with the initial layer formed by image piexls, spends too much time on the first meging step, especially when we applied it to high resolution remote sensing image. An effectively improved method is using a fast segmentation algorithm to create the initial object layer.

In this paper, we choose a graph based image segmentation algorithm, which runs in time nearly linear in the number of image pixels, to participate in our algorithm. The specific process is shown in Figure 2.

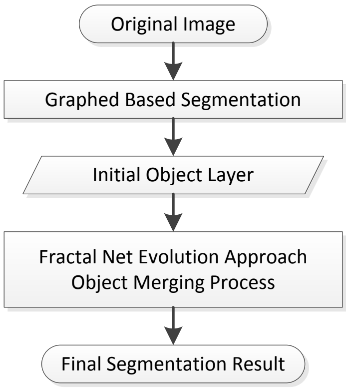


Figure 2. The process of our algorithm

An initial object layer can be obtained efficiently from graph-based segmentation. Then FNEA starts with the initial object layer and carries out the object merging process to get the final segmentation result.

3. GRAPH BASED IMAGE SEGMENTATION

Graph based image segmentation techniques generally represent the problem in terms of a weighted undirected graph $G = (V, E)$, where nodes correspond to pixels, and edges connect adjacent pixels. Each edge has a corresponding weight, which is a non-negative measure of the dissimilarity between adjacent pixels. The graph is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes output from these algorithms is considered an object segment in the image. Some popular algorithms of this category are minimum cut (Wu and Leahy 1993), average cut (Sarkar and Boyer 1996), normalize cut (Shi and Malik 2000, Kong et al. 2013), min-max cut (Ding et al. 2001), ratio cut (Wang et al. 2003) et al.
Felzenszwalb and Huttenlocher (2004) developed an efficient segmentation algorithm based on graph theory, and show that although this algorithm make greedy decisions it produces segmentation that satisfy global properties.
The internal difference of an object C is defined as:

$$Int(C) = \max_{e \in MST(C,E)} \omega(e) \tag{1}$$

where $\omega(e)$ means the weight of edge e in the minimum spanning tree.

Difference between two objects$\mathrm{C_1}$, $\mathrm{C_2}$ is defined as:

$$\mathrm{Dif(C_1, C_2)} = \min_{\mathrm{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E}} \omega(\mathrm{v_i, v_j}) \tag{2}$$

where $\omega(\mathrm{v_i, v_j})$ means the weight of edge connecting $\mathrm{v_i}$ and $\mathrm{v_j}$.

Criteria for merging two objects $\mathrm{C_1}$, $\mathrm{C_2}$ is defined as:

$$\mathrm{D(C_1, C_2)} = \begin{cases} \text{true} & \text{if } \mathrm{Dif(C_1, C_2) > MInt(C_1, C_2)} \\ \text{false} & \text{otherwise} \end{cases} \tag{3}$$

$$\mathrm{MInt(C_1, C_2)} = \min(\mathrm{Int(C_1)} + \tau(\mathrm{C_1}), \mathrm{Int(C_2)} + \tau(\mathrm{C_2})) \tag{4}$$

$$\tau(\mathrm{C}) = \mathrm{k}/|\mathrm{C}| \tag{5}$$

where $|\mathrm{C}|$ denotes the size of object C and k is some constant parameter.

An image is modelled to a graph $\mathrm{G = (V, E)}$, where are n vertices and m edges. S is the segmentation result, C is some object in S. The segmentation algorithm produces segmentation as follows:

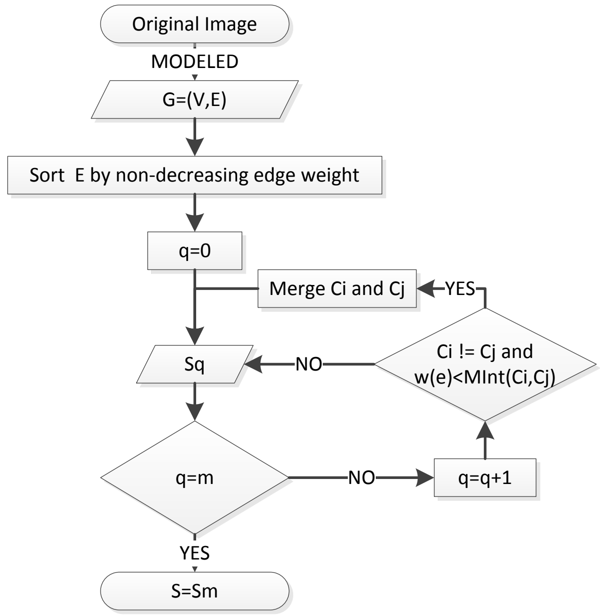


Figure 3. The process of graph-based segmentation

1) Sort E into $\pi = (\mathrm{e_1}, \ldots, \mathrm{e_m})$, by non-decreasing edge weight.
2) Start with a segmentation S^0, where each vertex v_i is in its own object.
3) Repeat step 4 for $\mathrm{q} = 1, \ldots, \mathrm{m}$.
4) Construct S^q given S^{q-1} as follows. Let v_i and v_j denote the vertices connected by the q-th edge in the ordering, i.e., $\mathrm{e_q} = (v_i, v_j)$. If v_i and v_j are in disjoint objects of S^{q-1} and $\omega(\mathrm{e_q})$ is small compared to the internal difference of both those objects, then merge the two objects otherwise do nothing. More formally, let C_i^{q-1} be the object of S^{q-1} containing v_i and C_j^{q-1} the object containing v_j. If $C_i^{q-1} \neq C_j^{q-1}$ and $\omega(\mathrm{e_q}) < \mathrm{MInt}(C_i^{q-1}, C_j^{q-1})$ then S^q is obtained from S^{q-1} by merging C_i^{q-1} and C_j^{q-1}. Otherwise $S^q = S^{q-1}$.
5) Return $S = S^m$.

4. MERGING CRITERION

The merging decision is based on a measure of the heterogeneity or some cost function. According to the character of different features in high resolution remote sensing image, we tried three different merging criterions for image objects based on spectral and spatial information.

4.1 eCognition Criterion

A merging cost, considered in eCognition, is described the change of heterogeneity in a virtual merge. $\mathrm{S'}$ would be the virtual merging object.
The increase of heterogeneity f has to be less than a threshold：

$$\mathrm{f = w_{color} \Delta h_{color} + w_{shape} \Delta h_{shape}} \tag{6}$$

where $\mathrm{w_{color}}$ and $\mathrm{w_{shape}}$ are the weight of spectral and shape, $\mathrm{w_{color} + w_{shape} = 1}$. $\mathrm{\Delta h_{color}}$ and $\mathrm{\Delta\, h_{shape}}$ are the increase of spectral and shape heterogeneity.
The increase of spectral heterogeneity $\mathrm{\Delta h_{color}}$ is defined as following：

$$\Delta h_{color} = n'\sigma' - (n_1\sigma_1 + n_2\sigma_2) \tag{7}$$

where σ and n are the standard deviation and size of object S, respectively.

The increase of shape heterogeneity Δh_{shape} is a value that describes the improvement of the shape with regard to smoothness and compactness of an object's shape. It is defined as following：

$$\Delta h_{shape} = w_{compact}\Delta h_{compact} + w_{smooth}\Delta h_{smooth} \quad (8)$$

where $w_{compact}$ is the weight of compactness, w_{smooth} is the weight of smoothness.

$$\Delta h_{compact} = n'l'/\sqrt{n'} - (n_1 l_1/\sqrt{n_1} + n_2 l_2/\sqrt{n_2}) \quad (9)$$

$$\Delta h_{smooth} = n'l'/b' - (n_1 l_1/b_1 + n_2 l_2/b_2) \quad (10)$$

where l is perimeter of object, b is perimeter of object's bounding box.

4.2 Fisher Criterion

Bilodeau et al. used a variant of Fisher's criterion to represent the heterogeneity between the adjacent objects, which is defined as follows:

$$F = \frac{|\mu_1 - \mu_{2|}}{\sqrt{\sigma_1^4 + \sigma_2^4}} \quad (11)$$

where μ and σ^2 are the mean and variance of object S, respectively.

In order to merge objects of close similarity as well as with large intersection. So we use the merging score formula:

$$\text{score} = \frac{|\mu_1 - \mu_{2|}}{\sqrt{\sigma_1^4 + \sigma_2^4}} \times \frac{P}{L} \quad (12)$$

where P is the perimeter of small object in S_1 and S_2, L is the common edge length of S_1 and S_2.

Given a object, we will find the smallest score among its neighbouring objects, and then merge the two obejcts if the score is less than a threshold and the common edge is not too small ($P/L < 5$).

4.3 Full λ-Schedule Criterion

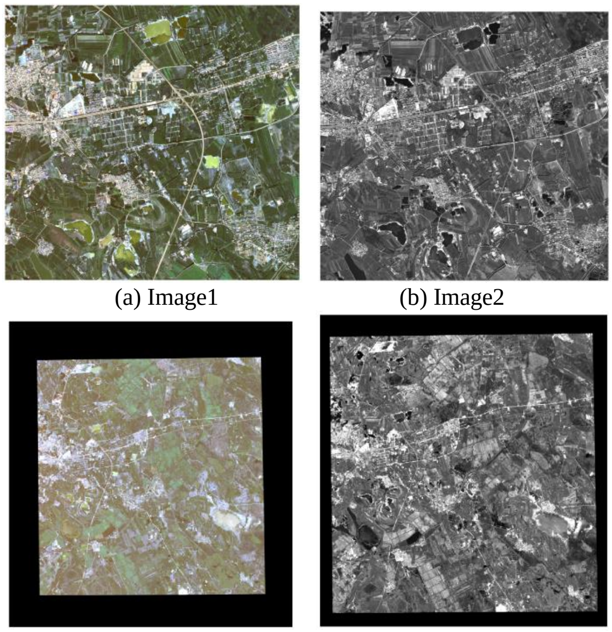
Robinson et al. proposed a novel fast implementation of the full λ-schedule algorithm for segmentation. In this algorithm, the decision to merge objects S_1 and S_2 occurs when t is less than a threshold where t is given by

$$t = \frac{\frac{n_1 n_2}{n_1 + n_2}(\mu_1 - \mu_2)^2}{L} \quad (13)$$

where μ and n are the mean and size of object S, respectively, L is the common edge length.

5. RESULTS AND ANALYSIS

We choose four WorldView-2 images which covering a study area in Heilongjiang, China. They are named as Image1, Image2, Image3 and Image4 and exposed in Figures 4. The information of the Images are presented in Table 1.



(a) Image1 (b) Image2 (c) Image3 (d) Image4

Figure 4. Images used for experiments

Name	Width	Height	Band	Size
Image1	3836	3561	4	105M
Image2	15341	14241	1	418M
Image3	10656	11424	4	929M
Image4	36704	39680	1	2.71G

Table 1. Images' information

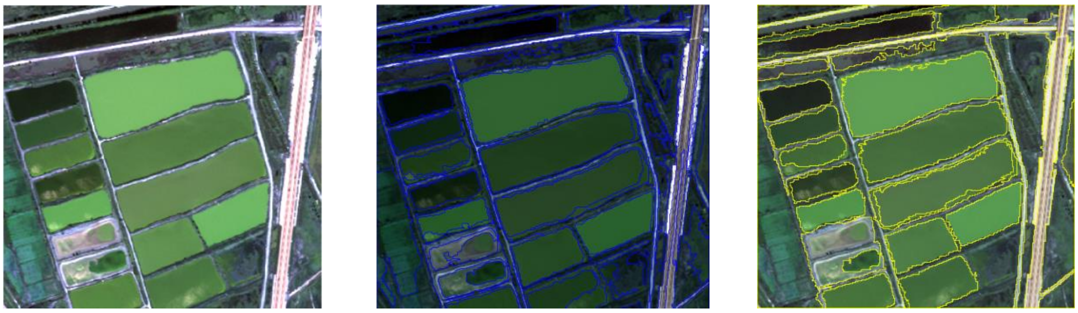
The performance of the proposed algorithm has been evaluated using the four images in our application, compared with FNEA in eCognition. The overall execution times of all images are compared in table 2.

Image	eCognition Time	Our Time
Image1	1min	1min
Image2	20min	15min
Image3	12min	10min
Image4	135min	54min

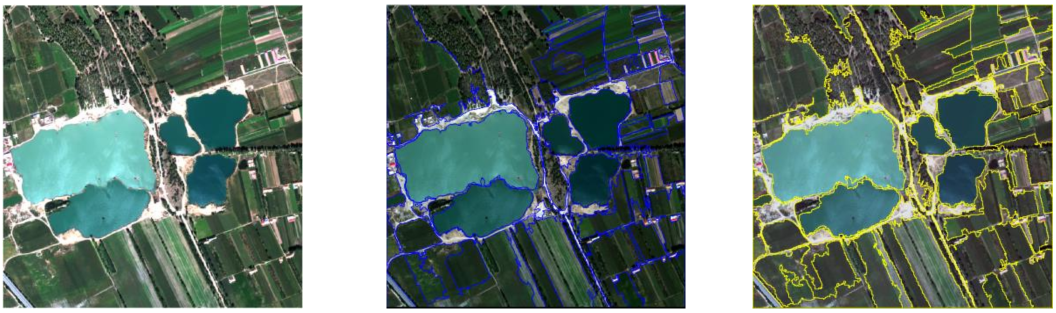
Table 2. Compared results of all images

As shown in this table, the speed of our algorithm is much better than eCognition, especially the size of image is large. When we use the image named Image4 in eCognition, the tips show that it spent 70 minutes on the first cycle to create the initial object layer, which nearly half of the whole time. Obviously, using a fast segmentation algorithm to create the initial object layer is a correct choice of improving the efficiency of the algorithm.

The details of the segmentation result are compared in Figure 5-7.



(a) Original image (b) Segmentation result of eCognition (c) Segmentation result of our algorithm
Figure 3. The segmentation result of vegetation



(a) Original image (b) Segmentation result of eCognition (c) Segmentation result of our algorithm
Figure 6. The segmentation result of water area

(a) Original image (b) Segmentation result of eCognition (c) Segmentation result of our algorithm
Figure 7. The segmentation result of buildings

We choose several different features in high resolution remote sensing image. Figure 5-7 show the segmentation result of vegetation, water area and buildings, respectively. It can be noted that our algorithm can maintain good feature boundaries in main areas and the extracted contours are consisted with the real edge of objects in the image.

6. SUMMARY AND CONCLUSIONS

Image Segmentation for high resolution remote sensing image is a crucial and essential step for object oriented image analysis. In this paper we proposed an efficient algorithm combined FNEA with graphed based image segmentation. Moreover, three different merging criterions were introduced to compute the heterogeneity of objects.
From the experiment result, we found the algorithm is much faster than the original FNEA, which is integrated in the commercial software eCognition.
Future work should focus on two issues. The first is using parallel processing to speed up the segmentation algorithm. The second is taking into account the texture features to compute the heterogeneity.

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