

The pixel rectangle index used in object based building extraction from high resolution images

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Abstract. An improved high resolution object-based building extraction method based on Pixel Rectangle Index is presented in this paper. We use Minimum Span Tree optimal theory to realize object-based high resolution image segmentation. First, we proposed a rotation invariant Pixel Rectangle Index by introducing the principal direction of homogeneous area. Second, we improved the calculation of edge-weight by introducing the band-weight and Pixel Rectangle Index. The QuickBird high resolution images were used to do the building extraction experiment. The experiment result proved that this method can obtain high extraction accuracy and this algorithm can be efficiently used in remote sensing images.

1. Introduction

Getting useful image objects is a fundamental procedure for higher level image processing such as successful image analysis and automatic image interpretation. Segmentation is recommended as the first step of object-based image analysis. The object-based high resolution image segmentation has been a new important subject with the increasing spatial resolution of IKONOS, QuickBird, OrbView sensors. In this paper, the object-based high resolution image segmentation is also a key question.

Shape character as a global topological feature, has been widely applied to image processing. Intra-class objects generally have the same or similar global shape and Inter-class objects, global shapes are different. Shape can distinguish different objects. What is more, shape is less susceptible to the influence of spectral, and has good robustness. Considering the spectral and shape characters, Baatz and Schape [1] use region grow and merge method which based on homogeneity definitions in combination with local and global optimization techniques realized multi-scale segmentation. That is the segmentation method used in eCognition software. Zhang, et al., [2] proposed a spatial feature index, pixel shape index, to describe the shape feature in a local area surrounding a pixel, they integrate both the spectral and shape characters using the support vector machine to classify high resolution images. Belongie, et al., [3] proposed a new pixel shape description method which calculated pixel context characteristics as the pixel shape features which is used to realized object recognition through shape matching. Andal, et al., [4] proposed a shape descriptor-Tensor Scale Descriptor with Influence Zones which unifies the representation of local structure thickness, orientation, and anisotropy which is used in content-based image retrieval tasks showing the good

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effectiveness. Shape feature all proposed based on a local area surrounding a pixel, which is used alone or with other features in image processing.

In this paper, we will introduce a graph based image segmentation method to realize high resolution remote sensing image segmentation. And make two improvements on it.

Graphs have been used as an important tool in Computer Vision due to their representational power and flexibility [5]. The image can be represented as an undirected, weighted graph $G(V,E)$ where each pixel in the image is considered as a vertex of the graph and an edge is formed between a pair of pixels which reflects the similarity of the pixels. This approach takes image segmentation as a graph partitioning problem which use graph optimal theory. In recent years, many graph based image segmentation methods have been proposed. They can be classified into two types, one is based on spectral clustering algorithms [6-11] which formulate the minimization of the optimal criterion as a generalized eigenvalue problem, it's too slow to be practical for many application [12]. Another type is directly graph reduction based on the classical graph optimal algorithms [12-17]. In all, we need to answer [6] two questions in graph based image segmentation as following:

1. What is the precise criterion for a good partition?
2. How can such a partition be computed efficiently?

Considering the high resolution remote sensing image characters and analyzing graph based image segmentation theory, we introduced the Minimum Span Tree (MST) algorithm to realize object based high resolution image segmentation. Felzenszwalb [12] developed an efficient segmentation based on MST, and proposed an pairwise region comparison predicate. In this paper, we introduce a new shape feature-pixel rectangle index which has rotational invariance. Another improvement is the calculation of edge-weight which is the first and key step in graph based image segmentation.

2. Pixel rectangle index

Zhang, et al., [2] proposed PSI(Pixel Shape Index) to examine the local structure of each pixel. Inspired by the idea, we proposed the rotational invariance pixel rectangle index which measures the rectangle degree of the homogeneous area which the pixel belongs to.

Pixel shape index extraction consists of three steps.

- a) *searching pixel homogeneous region based on spectral similarity*
- b) *measurement of the principal direction of homogeneous area*
- c) *calculation of pixel rectangle index*

2.1. pixel homogeneous area based on spectral similarity

The pixel homogenous area is used to reflect object's shape which the pixel belongs to. Taking current pixel as centric pixel, the spectral difference is measured between a pixel and centric pixel in order to decide if this pixel lies in the homogeneous area around the centric pixel.

The spectral homogeneity is defined using the following method similar to [2]:

$$D = \sum_{s=1}^n |p_s^{cen} - p_s^{sur}| \quad (1)$$

where D represents the spectral homogeneity between the centric pixel and its surrounding pixel, n denotes the number of spectral bands, p_s^{cen} is the spectral value of the centric pixel, and p_s^{sur} is the spectral value of the surrounding pixel.

In addition to the spectral homogeneity, the search scope meets size constraints by considering efficiency and effectiveness. When the search scope is too large, it will spend a lot of time; when the search scope is too small, we will not get the whole homogeneity area. In this paper, we will set size of the search scope by considering the size of object in high resolution images.

$$\begin{cases} T_1 \approx l_{obj} \\ T_2 \approx w_{obj} \end{cases} \quad (2)$$

where T_1 and T_2 represent the maximum length and maximum width of the search scope respectively; l_{obj} and w_{obj} denote the maximum length and maximum width of objects in high resolution images.

2.2. The principal direction of homogeneous area

Buildings in high resolution images have different directions. The pixel rectangle index has rotational invariance by considering the principal direction of homogeneous area. The principal direction is obtained by using Principal Component Analysis (PCA) of edge points of homogeneous area. Here, the principal orientation of the homogeneous area is computed as the angle of the eigenvector associated with the largest eigenvalue of the covariance matrix Σ which is defined as follows:

Let $(x_i, y_i)(i = 1, 2, \dots, n)$ represent boundary coordinates of homogeneous area.

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \quad (4)$$

$$\begin{cases} \Sigma_{11} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \\ \Sigma_{12} = \Sigma_{21} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \\ \Sigma_{22} = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 \end{cases} \quad (5)$$

Where

$$\begin{cases} \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \\ \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i \end{cases} \quad (6)$$

Then calculate the eigenvalue and eigenvector of covariance matrix Σ . Let λ_0 is the maximum eigenvalue and $U_0 = (x_0, y_0)^T$ is the eigenvector corresponding to λ_0 , the principal direction θ_0 of homogeneous region is defined as follows:

$$\theta_0 = \arctan \left| \frac{y_0}{x_0} \right|, 0 \leq \theta_0 \leq \pi \quad (7)$$

2.3. Calculation of pixel rectangle index

The pixel rectangle index is the rectangular degree which has rotation invariance by considering the principal direction of homogeneous area, which is defined as follows:

$$P = \frac{S_{obj}}{S_{rec}} \quad (8)$$

Where, P represents the rectangular degree, S_{obj} denotes the pixel number of homogeneous area and S_{rec} denotes the area of the minimum bounding of the homogeneous region. The directions θ_0 and its vertical direction are the directions of both sides of the minimum bounding.

3. Graph based segmentation

3.1. MST based segmentation

In graph based approach to segmentation, $G = (V, E)$ is an undirected graph with vertices $v_i \in V$, the sets to be segmented, and edges $(v_i, v_j) \in E$ corresponding to pairs of neighboring vertices. Each edge $(v_i, v_j) \in E$ has a corresponding weight $w(v_i, v_j)$ which is the distance (dissimilarity) between two vertices. A graph $G = (V, E)$ can be partitioned into disjoint sets, V_1, V_2, \dots, V_m , where

$$\bigcup_{i=1}^m V_i = V, \quad (8)$$

$$V_i \cap V_j = \emptyset, \quad i \neq j$$

This is the same as the image segmentation. Image pixels can be taken as the vertices, and the weight of an edge is some measure of the dissimilarity between two neighbor pixels connected by this edge.

A MST is a minimum-weight, cycle-free subset of a graph's edges such that all nodes are connected. In case of image segmentation, MST based segmentation is to find the MSTs (V_1, V_2, \dots, V_m) that satisfied some criterions which are in order to minimize the dissimilarity of the vertices' set in V_i . Felzenszwalb [12] presented an efficient MST based image segmentation algorithm which is related to the commonly used MST algorithm, Kruskal's algorithm, for constructing a MST of a graph. Kruskal's algorithm is a greedy algorithm that runs in polynomial time, and it can get the optimal solution. This makes it possible to be used in image segmentation.

In this method, there is one key problem need to be solved: How to measure the dissimilarity of two pixels? That is what we want to improved in the paper. In next section, we'll describe our work on this.

3.2. Band Weighted and Pixel Rectangle Index

Spectral curves reflect object's spectral characters in different bands. Different type objects have different kinds of spectral characters. This is why we select some bands combination to observer our interesting objects. So, we introduce the band weight to calculate the dissimilarity of pixels. Considering the high resolution remote sensing image characters, objects have obvious shape features. On the other hand, shape is less susceptible to the influence of spectral, and has good robustness. In this paper, we will combine spectral feature and shape feature(Pixel Rectangle Index) for high resolution images segmentation.

For example, Figure 1 showed one QuickBird high resolution image (a) and its Pixel Rectangle Index image (b), from them we can see Pixel Rectangle Index effectively reflects the rectangle degree of object that the pixel belongs to. Because large spectral heterogeneity, (b) is not complete enough. Pixels within the same target have similar pixel rectangle index. There is a large difference between object internal and edge. We can see obvious edge in pixel rectangle index image.



Figure 1. QuickBird image and its corresponding PRI image

So, we calculated the edge weight of two adjacent pixels using the following formula:

$$w(v_i, v_j) = \sqrt{\sum_{k=1}^n w_k (g_{kv_i} - g_{kv_j})^2 + w_{Shape} (P_{v_i} - P_{v_j})^2} \quad (9) \text{ where, } v_i \text{ represents the pixel of position } i; g_{kvi} \text{ is the pixel value of band } k \text{ in position } i; P_{v_i} \text{ is the pixel rectangle index of } v_i; n \text{ is the number of bands; } w_k \text{ is the band weight, } w_{Shape} \text{ is the shape weight, } w_k \in [0,1], w_{Shape} \in [0,1] \text{ and } \sum_{k=1}^n w_k + w_{Shape} = 1.$$

Each pixel in the image is considered as a vertex of the graph G. Edges are defined based on the adjacency relation of pixels. We constructed the graph by considering the 8-connectivity of the pixels. Figure 2 gives the weighted graph of image (a) in Figure 1. The left image is calculated without shape and all bands have the same band weight. The right two images are calculated with $w_{Shape}=0.5$, the other bands $w_k=0.125$. It is clear that weighted graph reflects the image edge. Weighted graph considering PRI get more complete building edges than that of not considering PRI.

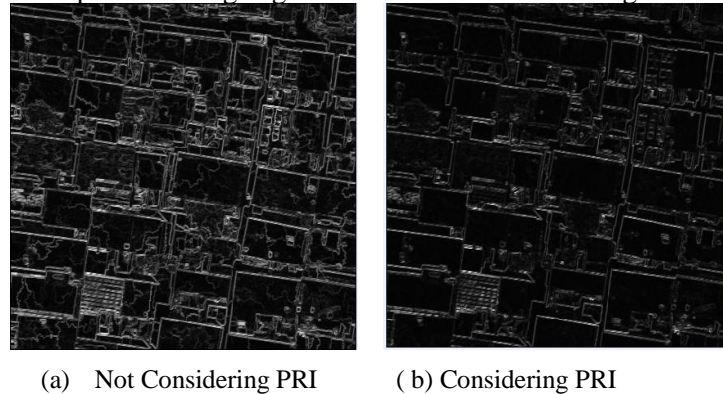


Figure 2. Weighted graph of image

4. Exprement result and analysis

4.1. Band Weighted and Pixel Rectangle Index

The aim of our introducing the band weight and Pixel Rectangle Index to edge weight is to make good use of the spectral and shape information of different objects. Pixel Rectangle Index is calculated through the formula (7).

Because Pixel Rectangle Index varies between 0 and 1, and the image pixel gray value is between 0 and 255, so we normalized Pixel Rectangle Index from $[0,1]$ to $[0,255]$.

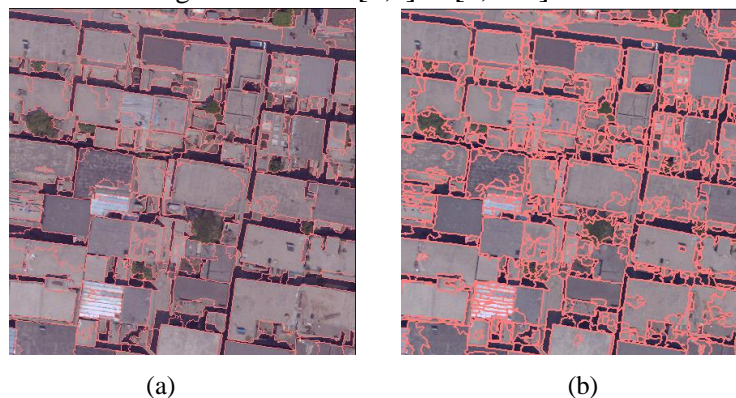


Figure 3. The segementation results of the original images in Figure 1. (a) represents the segmentation result considering PRI and spetal characistics; (b) is the segmentation result only considering spetal characteristic.

From figure 3, we can find that to compare with (b), segmented objects are more integrate in (a). As the large spectral heterogeneity in high resolution remote sensing image, most of buildings in (b) are segmented into several parts. But buildings in (a) are segmented more complete than (b). From this compare, we can conclude that the edge weight with Pixel Rectangle Index improved the segment accuracy.

4.2. Building extraction

In this paper, based on object-based idea and segmented results former, we will extract buildings by SVM which will use the object spectral characteristic. Here we give the extract result which using the mean value of all bands of the objects as their spectral characteristic. Figure 5 gives extraction results. We can see that almost all buildings are extracted completely. We can also draw a conclusion that PRI reflects the shape characteristic of buildings effectively from extraction results.



Figure 5. buliding extraction results

5. Conclusion

Overall, the paper proved Pixel Rectangle Index we proposed describes object's shape feature effectively which can be used in high resolution remote sensing images. Our proposal in the edge weight calculation with the addition of Pixel Rectangle Index and band weight can improve the segmentation accuracy. The segmentation results also show that our method keeps good objects boundaries. Building extraction object based has good extraction accuracy. In the future, we'll keep on studying more shape feature description methods which are used to objects extraction of high resolution images. On the other hand, we'll do more research on high resolution images analysis and interpretation.

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