A MULTI-SCALE SEGMENTATION METHOD FOR REMOTELY SENSED IMAGES BASED ON GRANULOMETRY

Z. Y. Jiang[a, *], X. L. Chen[a], Y. S. Li[b], C. Q. Chen[c]

[a] State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University , 129 Luoyu Road , Wuhan, 430079, CHINA, nundini@163.com
[b]Dept. of Civil and Structural Engineering, The Hong Kong Polytechnic University, Hong Kong, CHINA, ceysli@polyu.edu.hk
[c]LED, South China Sea Institute of Oceanography, Chinese Academy of Sciences, 164 Xingangxi Road, Guangzhou, 510301, CHINA, cqchen@scsio.ac.cn

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ABSTRACT

This paper proposed a multi-scale segmentation method for remote sensing image based on mathematical morphology. In mathematical morphological operations, opening transform can extract lighter connected components and closing transform can extract darker ones with size smaller than a given structure element in a gray image. A connected component, as an object, may have a high response to a given structure element size and a lower response to others. In this paper, granulometry and anti-granulometry were used for detecting the most sensitive element structures of objects from a range of structure elements with different sizes. Granulometry, an image sequence, was obtained by a series of opening transforms to the original image by using a family of structure elements with an integral index set. Anti-granuometry was generated by closing transforms. The resulting image sequences of granulometry and unti-granuometry were then operated by a series of derivatives , and the maximum value at each pixel corresponds to the index of the most sensitive structure element. The index was taken as the morphological characteristic of the corresponding pixel. The proposed segmentation method in this paper is based on the assumption that pixels with similar morphological features belong to the same connected component. This method avoids the problems of over-segmentation and boundary pixels occurred in the classical method of morphological segmentation.

1. INTRODUCTION

Mathematical morphology is based strictly on the mathematical theory, and its initial idea is to explore the structure of image by putting a structure element into it (Cui, 1999). The basic morphological operators include erosion, dilation, opening, closing, which were first systematically examined by Matheron and Serra in 1960s, and other operators can be defined by the above basic operators. Mathematical morphology has been applied successfully in many fields, such as medical imaging, material sciences, and machine vision (Cui, 1999), and many attempts were related to the processing of remotely sensed images, including segmentation (Pesaresi & Benediktsson, 1999), feature extraction (Talbot,1996; Vincent,1998; Katartzis, et.al, 2000), road network extraction on SAR image (Chanussot & Lambert, 1999) .

Image segmentation is a key step in image processing and analyzing. The object expression and feature detection in an image based on segmentation are required to express image in a more generalized form, which make it possible to analyze and understand image in a higher level (Zhang, 2001). In general, there are two fundamentally different strategies for image segmentation: edge detection and region growing. The standard approach to morphological segmentation is dependent on edge-detection (Pesaresi & Benediktsson, 1999), which segments image into different regions by the edge of structure, but has a problem for confirming which region the boundary pixels belong to. The approach of region growing tries to cluster pixels with same or similar features into one region.

The most classical segmentation method of mathematical morphology is the watershed segmentation. It gives a partition of image into catchment basins where every local minimum of the image belongs to one basin and the basins' boundaries are located on the "crest" values of the image (Geraud, et.al.,2001). However, the watershed algorithm usually leads to over-segmentation due to the presence of non significant local minima in the image, and therefore it cannot be applied directly except for a few simple cases where the target object is brighter than the background or vice versa (Pesaresi & Benediktsson,1999). Many solutions to the over-segmentation problem were proposed, eg, the selection of markers before flooding to reduce the infection of non significant local minima(Serra & Salembier,1993), or the merging of different basins after flooding to reduce regions obtained by watershed segmentation (Beucher,1994; Meyer,1994; Demarty & S.Beucher, 1998;). All the said approaches assume that the region of interest for detection is large and homogenous relative to the spatial and spectral resolution of the sensor. Consequently, these approaches are very difficult to be applied in segmentation of very complex scenes.

In this paper, a multi-scale segmentation method for remotely sensed image based on mathematical morphology is proposed. The idea is to characterize image structures by their morphological features obtained by morphological transformation. The pixels with the same characteristics in the image could be a connected component. This method avoids over-segmentation occurred in the watershed segmentation.

2. METHODOLOGY

2.1 Definition of Basic Concept and Operators

Infimum (□) and Supremum (□): The greatest lower bound is defined as infimum and the smallest upper bound as supremum for a particular set.

Structure Element ($N(p)$): It is the set of neighbors of a pixel *p* denoted as $N(p)$.

Erosion (ε_N) : Grey image $f(p)$ eroded by structure element *N*, is defined by the infimum of the values of the grey level function as follows:

$$\varepsilon_N f(p) = \left\{ \wedge f(p') \middle| p' \in N(p) \cup f(p) \right\} \qquad (1)$$

Dilation (δ_N) : Grey image $f(p)$ dilated by structure element *N* is defined by the supremum of the values of the grey level function.

$$\delta_N f(p) = \left\{ \vee f(p') \middle| p' \in N(P) \cup f(p) \right\} \qquad (2)$$

Opening (γ_N) : Erosion followed by dilation with the same structure element is denoted as opening:

$$\gamma_N f(p) = \delta_N \varepsilon_N f(p) \qquad (3)$$

Closing (φ_N) : It is defined as the result of dilation followed by erosion with the same structure element as follows:

$$\delta_N f(p) = \varepsilon_N \delta_N f(p) \qquad (4)$$

One of the characteristics of opening and closing operations is to erase objects smaller than the structure element. If the grey image can be considered as a topographical relief, then opening can cut the peaks (objects lighter than neighborhood), and closing can fill valleys (objects darker than neighborhood).

Top-Hat transform and inverse Top-Hat transform: The opening operation is anti-extensive, ie grey scale of every pixel in the opening processed image is not greater than that in the original image, and lighter objects smaller than structure element will be erased by opening operation. So the residual between original image and opening image can be defined as Top-Hat transform $(\Gamma f(p))$:

$$\Gamma f(p) = f(p) - \gamma_N f(p) = f(p) - \delta_N \varepsilon_N f(p) \quad (5)$$

This operation can extract the lighter objects smaller than the structure element.

The closing is extensive, ie grey scale of every pixel in the closing image is not smaller than that in the original image, and the valleys will be filled. So the residual between closing image and original image is denoted as inverse Top-Hat transform $(\Gamma' f(p))$:

$$\Gamma' f(p) = \varphi_N(p) - f(p) = \varepsilon_N \delta_N f(p) - f(p) \quad (6)$$

This operation can extract darker objects smaller than the structure element from the original image.

Structure element sequence: *N* dilated by itself successively to form a structure element sequence as follows:

$$\{N, N \oplus N, ..., nN\} \quad (7)$$

In order to record conveniently, the result dilated n times *nN* is replaced by *n* in the following calculation.

Granulometry and unti-granulometry: Granulometry proposed by Matheron is used for analysis of objects and structures in images. An image sequence $\{\gamma_n f(p), n = 1,2,3.......\}$ obtained by opening operations with a series of element structures $\{nN, n = 1,2,3....\}$, defined by equation (7), is taken as granulometry. If opening is replaced by closing, the image sequence $\{\varphi_n f(p), n = 1,2,3.......\}$ is called anti- granulometry.

2.2 Extraction of morphological features

The key step in the method proposed in this paper is to extract the morphological feature because the rule of segmention is based on the assumption that one connected component in the image will hold the same morphological feature. If a greyscale image is interpreted as topographical relief, pixels in the image can be approximately classified into three patterns: peak(lighter region),valley(darker region) and plain , which are respectively labeled as P □ V and P' .There are many objects with different sizes and shapes in an image, and some of them may have a high response to an element structure in a given size and a lower response for other size. In order to find out the most sensitive size for every pixel, the granulometry and unti-granulometry are used to get two image sequences $\{\gamma_\lambda(p), \forall\lambda \in [0,\cdots\cdots n]\}$ and $\{\varphi_\gamma(p), \forall\lambda \in [0,\cdots\cdots n]\}$ with the same structure element sequence. The derivative sequence of opening images can be defined as follows:

$$\Delta\gamma(p) = \{\Delta\gamma_\lambda(p) : \Delta\gamma_\lambda(p) = |\gamma_\lambda(p) - \gamma_{\lambda-1}(p)|, \forall\lambda \in [1,\cdots\cdots,n]\}$$

(7)

So there is a derivative vector $\Delta\gamma(x)$ at every pixel x:

$$\Delta\gamma(x) = \{\Delta\gamma_\lambda(x), \forall\lambda \in [1,\cdots\cdots n]\} \quad (8)$$

$\Delta\gamma_\lambda(x)$ is grey scale of $\Delta\gamma_\lambda(p)$ at pixel x. There is the greatest grey scale change when this image is processed by opening with the structure element corresponding to the supremum $\vee\Delta\gamma(x)$ at pixel x, i.e. the pixel x is most sensitive for this size structure element for the opening operation. So the multiscale opening feature at x is defined as:

$$\Phi_\gamma(x) = \{\lambda : \Delta\gamma_\lambda(x) = \vee\Delta\gamma(x)\} \quad (9)$$

Similarly, the multiscale closing feature at x is defined as:

$$\Phi_\varphi(x) = \{-\lambda : \Delta\varphi_\lambda(x) = \vee\Delta\varphi(x)\} \quad (10)$$

Based on the features above, the image segmentation algorithm can be denoted as:

$$\Phi(x) = \begin{cases} k_{\gamma\lambda} = \Phi_\gamma(x) : \vee\Delta\gamma(x) > \vee\Delta\varphi(x) \\ k_{\varphi\lambda} = \Phi_\varphi(x) : \vee\Delta\gamma(x) < \vee\Delta\varphi(x) \\ k_\lambda = 0 : \vee\Delta\gamma(x) = \vee\Delta\varphi(x) \end{cases} \quad (11)$$

where $\Phi(x)$ is the feature function. For the same structure element sequence, the greatest change of grey scale induced by opening operation is bigger than that by closing operation. When $\Phi(x) \in [1,2\cdots\cdots n]$, the pixel is considered as a lighter point, i.e peak; while $\Phi(x) \in [-1,-2,...-n]$, the pixel is taken as a darker point , i.e valley. For $\Phi(x) = 0$, the pixel belongs to a plain. The eigenvalue is concluded in a set $[-n,.....-2,-1,0,1,2,...,n]$. The pixels with the same feature are considered to be in the same region.

In case of uncertainty or ambiguity in distinguishing between scene foreground and background , it is also possible to soften the conditions of the morphological features by rewriting (11) as:

$$\Phi(x) = \begin{cases} k_{\gamma\lambda} = \Phi_\gamma(x) : \vee\Delta\gamma(x) - \vee\Delta\varphi(x) > \sigma \\ k_{\varphi\lambda} = \Phi_\varphi(x) : \vee\Delta\varphi(x) - \vee\Delta\gamma(x) > \sigma \\ k_\lambda = 0 : |\vee\Delta\gamma(x) - \vee\Delta\varphi(x)| \le \sigma \end{cases} \quad (12)$$

where σ is a threshold value.

3. Results and discussion

In this paper the IKONOS image in Shenzhen of China with the spatial resolution of 4*4 (Fig.1) was selected. The objects in the image are labeled with different morphology features which are the sizes of the structure elements. The image was segmented and coded at the same time according to morphology feature. The proposed segmentation algorithm was implemented by VC++ programming. The primary objects in an image include buildings, streets, green belts, rivers and ponds.

In this method, the selection of structure elements is very important. The structure elements with different shapes and sizes should generate different results. The result obtained by octagonal structure elements is better than that by square structure elements which have been proved by experiments by others. In this paper, a structure element sequence formed by two octagonal structure elements denoted as N_1 and N_2, where

$$N_2 = N_1 \oplus N_1 \qquad (13)$$

The diameters of the two structure elements are 7 and 13 pixels and σ is 5. Five resultant images could be obtained after segmentation (figures 2-6), and the black part includes pixels with same morphological features. Figs. 2 and 3 show the peaks with different features. In Fig.2, the light objects smaller than N_1 mainly consist of buildings, while the light objects greater than N_1 but smaller than N_2 appear in Fig.3. Some pixels belonging to plains, which have a lower response to the structure elements in a given size, can be found in Fig.4. The objects included in Fig.4 are related to the selection of threshold value σ, a greater σ means more objects will fall into this image. As rivers and ponds are homogeneous in a large area that are bigger than the structure elements in given sizes, they have a lower response to the structure elements. In general, if the size of the given structure element is great enough (larger than these objects), the objects will belong to valley images because these objects are very dark (local minimum) in the image. Figs. 5 & 6 consist of valleys with different morphological features. Some small and dark objects are mainly included in Fig.5, such as grass plots and shadows between buildings and some streets within residential areas. Grass land and greenbelts located on both sides of roads in bigger areas are shown in Fig. 6.

Fig.1 IKONOS image in Shenzhen, China

Fig.2 Light objects sensible to structure element N_1

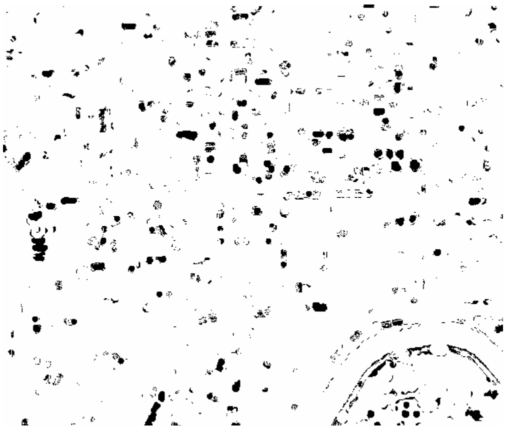

Fig.3 Light objects sensible to structure element N_2

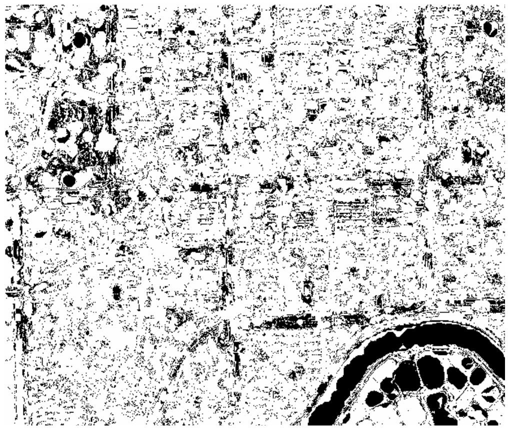

Fig.4 Objects insensible to the structure element sequence

Fig.5 Dark objects sensible to structure element N_1

Fig.6 Dark objects sensible to structure element N_2

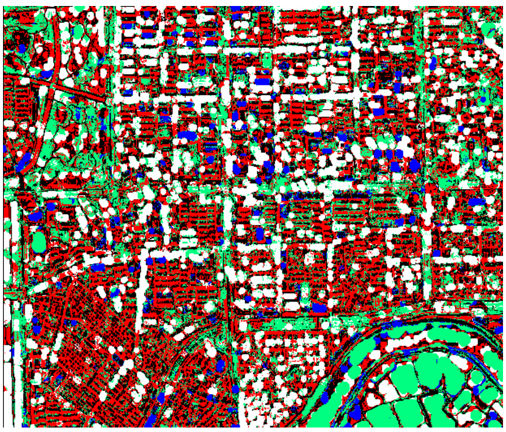

Fig.7 Result obtained by the proposed method in this paper

Fig.8 Result obtained by the watershed segmentation

The results of multi-scale segmentation to remotely sensed image are shown in Fig. 7. In this resultant image, the buildings, water, grassland and roads can be basically distinguished. Fig. 8 is the result of watershed segmentation, which is calculated by Matlab. It can be seen that over segmentation and boundary pixels spoiled the results. Compared with Fig. 8, the segmentation approach proposed in this paper is better than classical watershed segmentation, because the algorithm here avoids the problems of over segmentation and boundary pixels by obtaining morphology features of objects. Different types of objects can fall into different resultant images. In this way, the original image can be effectively segmented.

4、Conclusions

In this paper, we present a novel approach for multi-scale segmentation of images, which is based on granulometry and anti-granulometry. Through derivatives within an image sequence, we can get the morphological feature of the image on which the image segmentation is performed. In this method we presume that pixels with same morphology features belong to the same object. Experiments show that the proposed approach is more effective than the watershed method. The problems of the boundary pixels and over segmentation are avoided because the algorithm is based on the regional feature. This method fits to segments of remotely sensed images with higher spatial resolution.

From this study, the following problems still need to be further addressed.
Selection of structure element: The objects in reality are complicated and have various shapes so that the structure element can be selected in many ways. The selection of suitable structure elements is a key step for analyzing morphological features. It is impossible for structure elements with a single shape and variable sizes can suit all objects in the image. We should study whether a multi-shape structure element sequence can be used.

The morphological feature of every pixel was assumed to be unique in the algorithm of this paper. When the image possesses complex objects, some pixels may have more than one significant derivative maximum, i.e., morphological feature of every pixel is not unique. In this case, it is a problem to classify the morphological feature of the pixel.

Selection of parameter σ under soften condition: The parameter σ reflects the sensitivity of objects to structure elements. If the parameter is suitable, we can obtain good results of image segmentation under a certain sequence of structure elements. We need to further study the relations among shape and size of structure elements, parameter σ and image.

The morphological feature obtained by the algorithm proposed in this study reflects the structure and size of objects in the image. The shape and size of objects in the resultant image would be influenced heavily by the structure elements. So the resultant image may provide some false information if the structure elements are not selected properly. A possible improvement is to consider segmenting images through cluster vectors formed by morphological and other image features.

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