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Feature Based Approach For Segmenting Remote Sensing Images

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Abstract—In remote sensing, observation data are available with increasingly high spatial and spectral resolution, object-based image analysis approaches receive more and more attention. Object-based analysis uses regions or segments of an image as basic units. Segmentation provides building blocks for object-based analysis. Image segmentation partitions an image into non overlapping regions so that each region is as homogeneous and neighboring ones as different as possible. Multispectral (MS) images are the main type acquired by remote sensing radiometers. Here a bank of filters are used. So there uses local spectral histogram representation which consists of histograms of filter responses in a local window. To address the high dimensionality and boundary localization problems, proposed segmentation method is multivariate linear regression. Segmentation is linked to the scale issue. Meaningful structures and objects exist over a certain range of scales. Improper scales leads to oversegmentation and under segmentation.

Index Terms— Multispectral(MS), Medial Axis(MA), Medial Axis Transform(MAT), Single Value Decomposition(SVD).

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1 Introduction

Object-based image analysis approaches receives more and more attention in analyzing remote sensing data[2]. In contrast to traditional pixel-based analysis, object-based analysis uses regions or segments of an image as basic units, which has a number of benefits, including reduced spectral variability and more spatial and contextual information such as shape and topological relationships. A key step in object-based analysis is image segmentation, which partitions an image into nonoverlapping regions so that each region is as homogeneous and neighboring ones as different as possible. Segmentation provides building blocks for object-based analysis. Image segmentation has been extensively studied. In remote sensing, a segmentation method should leverage the advances made in data acquisition, specifcally the spectral and spatial resolution capability. Multispectral (MS) images, which are the main type acquired by remote sensing radiometers, provide much enhanced capabilities of characterizing ground objects. Meanwhile, high-resolution images contain rich texture information, which has been shown to improve segmentation results. Therefore, remote sensing segmentation methods are expected to make use of both spectral and texture information[1].

It is widely recognized that a visual texture is very difficult to characterize. In remote sensing image analysis, morphological transformations are often employed to deal with texture information. However, morphological operations have limited forms and, thus, lack the ability to describe complex textures. Semivariograms, which quantify spatial variability, are frequently used for texture analysis in geospatial data. The main drawback of using a semivariogram as a texture descriptor is the high computational cost, which makes it impractical for large images. Texture analysis shows an emerging consensus that an image should be first convolved with a bank of filters tuned to various orientations and spatial frequencies. Texture descriptors constructed by analyzing the local distribution of filter responses have been shown to be powerful features for texture synthesis and discrimination. With such texture descriptors, one can develop a combined spectral and texture segmentation framework by feeding integrated features to clustering approaches to produce segmentation. However, there are two main problems associated with such framework. First, applying multiple filters to spectral bands generates high-dimensional features. As a result, not only is the computational cost high, but many clustering methods also fail to work for high-dimensional data. The second problem stems from texture descriptors generated from the image windows crossing multiple regions, which cause difficulty in localizing region boundaries.

Using local spectral histogram representation[3], which consists of histograms of filter responses in a local window. This representation provides an effective feature to capture both spectral and texture information. However, as a form of texture descriptors, local spectral histograms also suffer from the problems of high dimensionality and boundary localization. To address these problems, segmentation as multivariate linear regression are formulated[4]. This method works across different bands in a computationally efficient way and accurately localizes boundaries. With remote sensing images, segmentation is inextricably linked to the scale issue. Conceptually, scale is a window of perception[5]. It is well known that meaningful structures and objects exist over a certain range of scales. In image processing, a scale usually refers to the size of the operators or measurement probes used to extract information from image data. Improper scales can lead to oversegmentation, where segments correspond to portions of regions, or undersegmentation, where one segment contains multiple landcover classes. Due to the inherent multiscale nature of real-world objects, many multiscale segmentation algorithms have been proposed. However, manual interpretation is typically needed in order to utilize the segmentation results at multiple levels, which inevitably involve subjectivity. Moreover, it has been shown that, in specific cases, single-scale representation might be sufficient and more straightforward. A scale selection method is to appropriately characterize spatial patterns and give a controlled smoothing effect.

2 Proposed Segmentation Method

Remote sensing image segmentation, which utilizes both spectral and texture information are used. Here local spectral histogram features are utilized to produce accurate segmentation.The results can be easily improved by incorporating additional information such as shape and context[11].This can be enhanced by a simple technique, which is to compute the medial axi s of each connected segment and assign those with long medial axes and small associated radii to each segment. The method has three stages such as image segmentation using Multivariate linear regression, medial axis extraction within each segment and selection of points located in potential areas.

After image segmentation, the medial axis points of segments are extracted, and candidate points are selected. Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated. For example, in the automated inspection of electronic assemblies, interest lies in analyzing images of the products with the objective of determining the presence or absence of specific anomalies, such as missing components or broken connection paths. There is no point in carrying segmentation past the level of detail required to identify those elements. Segmentation is performed in two steps. The first step is designed for regions and produces large and smooth segments. The second step is designed to be sensitive to boundaries which tend to be missed in the first step, and this step segments narrow areas with clear edges.

After segmentation of an image, the medial axis transform is employed. The concept of the medial axis transform is to transform a 2-D object into a 1-D line representation that largely preserves the extent and connectivity of the original object. The medial axis of an object is defined as the loci of the centers of all circles that touch the boundaries at two or more points. The radius of the circle recorded at a point of the medial axis provides information about local thickness. The shape of the original object can be recovered by plotting circles at all the medial axis points. A common approach to compute the medial axis is the Voronoi diagram. Given a set of points S in a plane, the Voronoi diagram is a partition of the plane into cells, each of which contains all the points in the plane closer to one particular point in S than to any others. It has been pointed out that the vertices of the Voronoi diagram for a set of samples on a boundary curve in the object approximate the medial axis. The more densely the space is sampled, the more accurate the medial axis is.

The Medial Axis (MA), or skeleton of the set D, denoted M(D), is defined as the locus of points inside D which lie at the centers of all closed balls (or disks in 2-D) which are maximal in D, together with the limit points of this locus. A closed ball (or disk) is said to be maximal in a subset D of the 3D (or 2D) space if it is contained in D but is not a proper subset of any other ball (or disk) contained in D. The radius function of the MA of D is a continuous, real-valued function defined on M(D) whose value at each point on the MA is equal to the radius of the associated maximal ball or disk. The Medial Axis Transform (MAT) of D is the MA together with its associated radius function. The MAT can be constructed from the bisectors (locus of equidistant points) of the entities on the domain boundary. Using the exact representation of the part for constructing the MAT eliminates the need for additional processing required to eliminate the artificial segments that may arise due to the discretisation of the curved entities into polyhedral entities. Conditions that determine a point on MAT is the distance criterion. Any point on a seam (apart from the other points of the MAT) should be equidistant to three different boundary segments. This is equivalent to saying that any point on the simplified segment of MAT in 2D (apart from the terminal points) should be equidistant to two boundary segments. To apply medial axis transformation, first find the distance from particular pixel to the closest boundary. For each pixel in the image, this function will computes the Euclidian distance between that pixel and the nearest nonzero pixel of the image. Computed values will be assigned to that pixel after doing the distance transformation to the image, use the resulting image to analyze which pixel is in the medial axis of the image. Technically, find the local maximum in row and column from the distance transformed image and then flag it as the skeleton of the image.

A closing operation is first performed to smooth the boundary. Closing is defined as a dilation operation where each background pixel next to an object pixel is changed into an object pixel, followed by an erosion operation where each object pixel next to a background pixel is changed into a background pixel. By treating the boundary pixels of segments as the samples, the medial axis points of each segment are obtained from the Voronoi diagram. Each medial axis point with its radius indicates the position and size of the region that it lies in. A medial axis point is selected as a candidate if its radius is sufficiently small. The radius threshold is determined. Medial axis points are selected instead of segments and thus, selection based on medial axis points gives more accurate results.

The closing of set A by the structuring element B is defined by:

$$A \bullet B = (A \oplus B) \ominus B$$

Closing also tends to smooth sections of contours but, as opposed to opening, it generally fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gapsin the contour. It is defined simply as a dilation followed by an erosion using the same structuring element for both operations. Closing cannot be done multiple times. Thinning is a morphological operation that is used to remove selected foreground pixels from binary images, somewhat like erosion or opening.
The thinning operation is related to the hit-and-miss transform.

$$\mathrm{thin}(I, J) = I - \text{hit-and-miss}(I, J)$$

where the subtraction is a logical subtraction defined by :

$$X - Y = X \cap \mathrm{NOT}\ Y$$

The choice of structuring element determines under what situations a foreground pixel will be set to background, and hence it determines the application for the thinning operation.

3 Result And Analysis

The experimental study and comparison will be applied on a number of remote sensed images. After applying the multivariate linear regression for segmentation, medial axis transformation is performed by incorporating more features to improve the results. The sample images used are as follows:

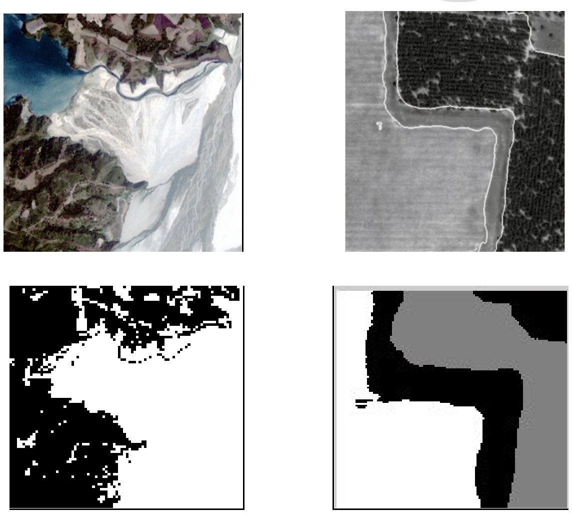

Fig.1. Sample Input Images (1st row); Segmented Images (2nd row)

4 Conclusion

Object based image analysis is a relatively new approach to remote sensing image analysis, where the basic units, instead of being individual pixels, are image objects. Here remote sensing images segmentation based on spectral and texture features use local spectral histograms to provide combined features. By regarding each feature as a linear combination of several representative features, the segmentation problem as a multivariate linear regression
formulated, which can be solved by least squares estimation. Also proposed methods based on SVD to automatically estimate representative features and select proper scales. The experimental results on different image sets are encouraging. In most cases, the problem of performance degradation with complex scene can be tackled by a divide-and-conquer strategy. A more general approach is to impose constraints on a least squares solution, making it more robust to noise. The results can be easily improved by incorporating additional information such as shape and context. This can be enhanced by a simple technique, which is to compute the medial axis transformation. After image segmentation medial axis extraction within each segment is performed and selection of points located in potential areas which give more accurate results.

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