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Nonlinear Processing of Large Scale Satellite Images via Unsupervised Clustering and Image Segmentation

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Abstract: **–** For large scale satellite images, it is evitable that images will be affected by various uncertain factors, especially those from atmosphere. To minimize the impact of atmosphere medium dispersing, image segmentation is an essential procedure. As one of the most critical means of image processing and data analysis approach, segmentation is to classify an image into parts that have a strong correlation with objects in order to reflect the actual information collected from the real world. The image segmentation by clustering basically refers to grouping similar data points into different clusters. In this article, an unsupervised clustering technology is proposed for processing large scale satellite images taken from remote celestial sites where none explicit teacher is introduced. As an effective approach, K-means clustering method requires that certain number of clusters for partitioning be specified and its distance metric be defined to quantify relative orientation of objects. Then image processing system forms clusters from input patterns. Diversified large scale image features are investigated using unsupervised methods. At the same time, to limit computational complexity for real time processing consideration, a simple study is also conducted where tristimulus values are selected to represent three-layer color space. Simulation results show that this approach is very successful for spatial image processing.

Key-Words - Large scale satellite image, K-means clustering, Image segmentation, Nonlinear processing.

1 Introduction

Large-scale spatial data management is a highly nonlinear and comprehensive task for processing of remote celestial images. For a given large-scale spatial image, the key step to analyze all the intrinsic information involved is image segmentation, that is, how to segment the image into one group of smaller images with some indexes for each of them (e.g., layout feature, color feature or shape feature). In other words, how to recognize, extract and discriminate useful image information on a basis of some typical reference images, such as the urban image, countryside image, forest image, bridge image, road image, water image, and so on. Image segmentation acts as a resource by which the object content can be uncovered. So far, there is no universal segmentation approach that is appropriate for given images under every possible circumstance. Numerous techniques have been proposed over a variety of image types. The wide variability makes it difficult to bring forth a sole acceptable solution to many diversified problems.

A great deal of research on image segmentation has been proposed, conducted and then testified during the past years. Samadani proposed a computer-assisted boundary extraction approach, which combined manual inputs from the user with image edges generated by the computer [1]. Daneels developed an improved method of active contours. Based on the user's input, the algorithm first used a greedy procedure to provide fast initial convergence. Secondly, the outline was refined by using dynamic programming [2]. Rui et al. proposed a segmentation algorithm based on clustering and grouping in spatial-color-texture space. The user defines where the attractor (object of interest) is, and the algorithm groups regions into meaningful objects [3]. Lots of other approaches also showed many convincing results [1-16]. For instance, multi-scale techniques for image segmentation have been conducted with satisfactory results [4].

It should be pointed out that various methods of image segmentations have been explored, both on computer vision applications and currently on image retrieval applications. Most of research mentioned above is focused on specified small size images at the image databases. For the large-scale spatial image data, image enhancement occurs in spatial domain, which turns out to be a new area. So far no fast and efficient technique has been exploited to extract information from huge image data. To effectively synthesize all essential information, K-means clustering based image segmentation is investigated to seek for the detail information of satellite images. In addition, a simplified K-means clustering case is also tested to reduce computational complexity, which is corresponding to intuition sense of the people.

2 Image Segmentation

Image segmentation is used to accumulate similar pixels together to form a set of coherent image layers or regions from an individual image given. Information noise and image ambiguity are two common issues that are in need of image segmentation. As for satellite images, atmosphere dispersing issue is topmost important to consider. In most cases, the pixel similarity can be measured based on the consistency of location, orientation, intensity, brightness, color and texture of different pixels. In general, elements can be either collected together to represent an image pixel or partially used to some extent. For example, information of color can be used exclusively at first and so does location or intensity. Main approaches are global segmentation and partial segmentation. Former one is a complete procedure and the latter is an incomplete one. Usually global approach uses histogram of image features. Each layer or regions is uniquely associated with objects in the original image. Partial segmentation does not associate with image objects directly. Images are divided into separate parts that are homogeneous with respect to property of brightness, color or texture, etc. One reasonable method is to use partial segmentation as preprocessing procedure prior to a higher level processing. The large scale spatial image is a complex and complicated scene itself. Global image segmentation is proposed for large scale data processing. First of all, distance metric must be defined to be a criteria related to the final decision making. Then K-means clustering is proposed for image segmentation in terms to the distance metric and the decision rule. Furthermore, special simplification case study of K-means clustering is presented to be an alternative in order to reduce the computational complexity.

3 Distance Metric via Color Histogram

All the color histograms being used are normalized, that is, color histograms are given by percentages instead of true values. Accordingly, a large-scale spatial satellite image is partitioned into the n×m smaller subsets. Two ways for partitioning a large-scale spatial image are considered as belows: Fixed block size and Quadtree (Fig.1).

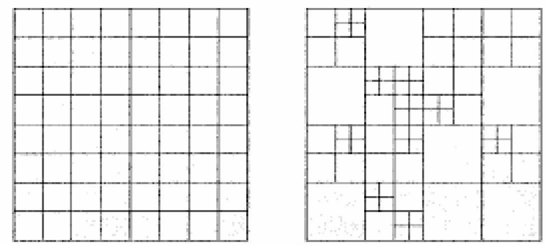

Fig 1. Fixed block size (left) and Quadtree (right)

Based on spatial color histogram for the reference images $I_{r\_i}, i = 1,2,...k$ and subsets $I_{m\_j}, j = 1,2,...n \times m$, the metric measurement is considered by two facts: spatial color histogram and spatial color histogram varying differences, which are defined as A and B, respectively.

A. Distance measurement on reference image I_{r_i} and subset I_{m_j} for spatial color histogram:

$$d(h_{I_{r\_i}}, h_{I_{m\_j}}) = \frac{\sum_{n=1}^{N} (h_{I_{r\_i}}(n) - h_{I_{m\_j}}(n))^2}{\sum_{n=1}^{N} (h^2_{I_{r\_i}}(n) + h^2_{I_{m\_j}}(n))} \quad (1)$$

B. Distance measurement on reference image I_{r_i} and subset I_{m_j} for spatial color histogram varying differences:

$$d(d_{I_{r\_i}}, d_{I_{m\_j}}) = \frac{\sum_{n=1}^{N-1} (d_{I_{r\_i}}(n) - d_{I_{m\_j}}(n))^2}{\sum_{n=1}^{N-1} (d^2_{I_{r\_i}}(n) + d^2_{I_{m\_j}}(n))} \quad (2)$$

where $d(n) = h(n) - h(n-1), n = 2,3,,,,N$

The whole metric measurement is

$$d(I_r, I_{m\_j}) = \min_{i=1,2,...k} (\lambda d(h_{I_{r\_i}}, h_{I_{m\_j}}) + (1-\lambda) d(d_{I_{r\_i}}, d_{I_{m\_j}})) \quad (3)$$

where $0 \le \lambda \le 1$ is a non-negative,adjustable parameter. The regions to be segmented are decided by (4):

$$\Omega_j : j = 1,2,...n \times m : \begin{cases} d(I_r, I_{m\_j}) \le \rho, & (I_{m\_j} \in I_r) \\ d(I_r, I_{m\_j}) > \rho, & (I_{m\_j} \notin I_r) \end{cases} \quad (4)$$

The Quadtree with varying squares gives an efficient result, which is to be used in context.

4 K-Means Clustering Algorithm

Clustering is a pattern recognition process of partitioning a set of pattern vectors into subsets called clusters. Cluster analysis divides sample data into several groups so that the similar data objects belong to the same cluster and different data objects belong to separate clusters. As an unsupervised learning algorithm, K-means clustering algorithm has the potential to simplify the computation and accelerate the convergence, where K is the number of cluster centers. Now the center of each cluster is defined as C_i to represent that cluster. The procedure follows an easy way to classify the data sets through K number of clusters. The center of each cluster is the mean of the data points which belongs to the cluster. Then a distance measurement D(x,y) is defined as the similarity measurement. The distance of a data point to these cluster centers has been compared such that a data point will belong to its nearest cluster:

$$l_k(x_k) = \arg\min_i D(x_k, C_i) = \arg\min_i \|x_k - C_i\|^2 \tag{5}$$

where l_k is the label for a data point x_k. The K-means algorithm tries to find a set of cluster centers so that the total distortion is minimal. Here, the distortion is defined by the total summation of the distances of data points from its cluster center (6).

$$\phi(\mathcal{X}, \mathcal{C}) = \sum_{i \in \mathcal{C}} \sum_{j \in \mathtt{i-th\ cluster}} ||x_j - C_i||^2 \tag{6}$$

To minimize the distortion ϕ, K-means algorithm iterates between two steps: labeling and re-centering.

A. For labeling, assume the p-th iteration ends up with a set of cluster centers $C_i^{(p)}, i = 1,2,...K$. Each data point is labeled on a basis of a set of cluster centers, i.e., $\forall x_k$, find $l_k^{(p+1)}(x_k) = \min_i ||x_k - C_i^{(p)}||^2$ (7)

and group data points belong to the same cluster:

$$\Omega_j = \{x_k : l_k(x_k) = C_j\} \tag{8}$$

B. For re-centering, calculate centers for all clusters

$$C_i^{(p+1)} = \frac{\sum_{x_k \in \Omega_i} x_k}{|\Omega_i|} \tag{9}$$

This algorithm iterates between labeling and re-centering steps until it converges to a local stationary.

In the following cases, each pixel from a satellite image results from 2m × 2m spot of earth which also represents a particular watershed area.

5 Case 1: 2m×2m/pixel Spatial Image

The proposed segmentation approach is to be testified in this section. A large scale spatial image (2m×2m/pixel) indicates the area around Oak Ridge. Watershed area can be located by comparing with the actual local map. Results illustrated are still ambiguous raw data due to the size of its segmented areas (e.g. tree areas in a 2 meter range, hill area in a 30 meter range). Detailed procedure needs to be taken into account to refine the segmented data to eventual segmented areas. The final refining processing is shown below, where satisfactory results are obtained for large-scale spatial image data segmentation. Some features associated with the spatial color histogram can be considered as a new retrieval index.

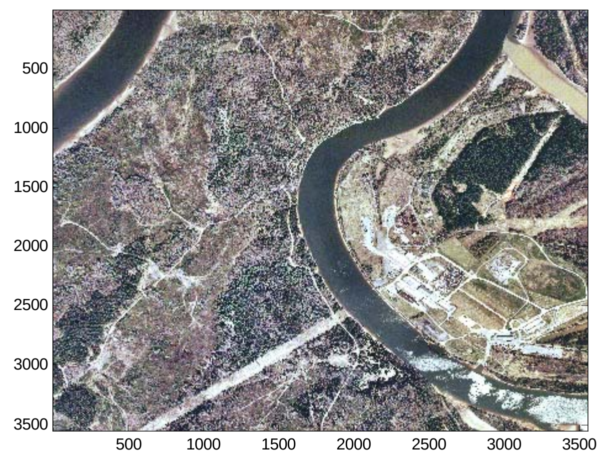

Fig 2. Original Image of Oak Ridge (2m×2m /pixel)

Fig 3. Water Area Segmented by Color Histogram

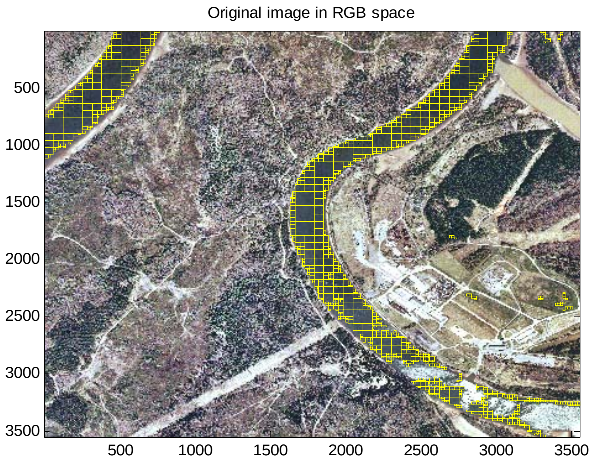

Fig 4. Water Area (Yellow Squares)
Segmented by Color Histogram Method

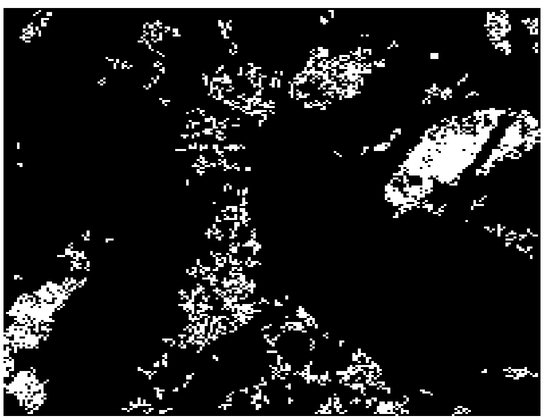

Fig 5. Green Tree Area
Segmented by Color Histogram Method

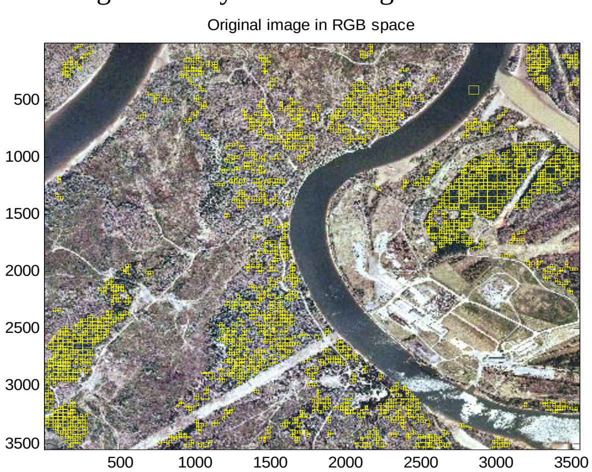

Fig 6. Green Tree Area (Yellow Squares)
Segmented by Color Histogram Method

Fig 7. Plant Tree Area
Segmented by Color Histogram Method

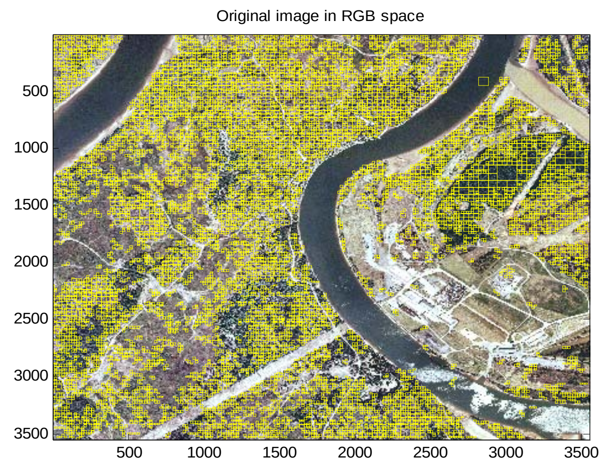

Fig 8. Plant Tree Area (Yellow Squares)
Segmented by Color Histogram Method

Figure 3 through Figure 8 shows that actual color histogram segmentation methods work well on 2m×2m/pixel images. In fact, this method requires numerous regions or layers to be defined beforehand. Considering computational difficulty and processing time of large scale spatial data, complexity reduction is necessary in order to achieve the potential real time processing. For each input object, k-means clustering returns an index corresponding to a cluster. On the other hand, computational complexity normally is closely related to the number of clusters and it increases rapidly as the cluster number goes up. Consequently, the three layer case is investigated according to the sense of vision. In following section, another satellite image will be processed using three layer K-means clustering.

6 Case 2: Clustering by Tristimulus Value

Clustering is the approach that separates groups of objects. K-means clustering assigns each object a space location. One significant consideration affecting an image processing design methodology is computational complexity, which in fact reflects the difficulty of image processing computation. Processing of large scale satellite images is a process of image enhancement in spatial domain. The procedure for feature capturing and restoration sometimes has a necessity of real time processing. Thus the computational complexity must be considered in advance. As a matter of fact, three-layer color space is selected on a basis of tristimulus values into K-means clustering algorithm. This color space consists of red-green chromaticity layer, blue-yellow chromaticity layer and luminosity layer. For all three layers, partition is conducted in such a way that objects within each cluster are as close as possible to each other, and vice versa, as far as possible from objects in other clusters.

Fig 9. Original Image of Yangtze River

Mahalanobis distance is used as measurement of distance metric, which is simply defined as:

$$d = (s - X_A)^T K_A^{-1} (s - X_A) \qquad (10)$$

where X_A is cluster center of any layer A, s is any point, d is Mahalanobis distance, K_A^{-1} is inverse of covariance matrix.

Fig 10. Cluster of Yangtze River Image (1)

Fig 11. Cluster of Yangtze River Image (2)

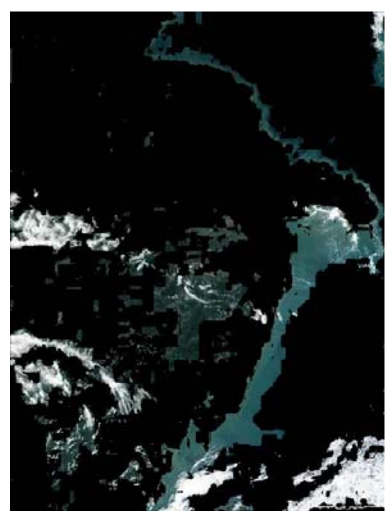

Fig 12. Cluster of Yangtze River Image (3)

7 Conclusion

The proposed method has been implemented as the content-based large-scale image segmentation. Through K-means clustering using criteria from defined distance metric, the satellite images (2m×2m /pixel) are processed and analyzed, while selected objects (e.g, rivers and trees) are successfully clustered. Moreover, the feasibility of reduced dimension K-means clustering is testified, which is based on Tristimulus Value method out of human sense. Spatial color histograms for three layers are formulated and simulation results are satisfactory. Hence, the desired level of segmentation has been achieved via both spectrum oriented algorithm and object oriented algorithm. A thorough image processing and restoration procedure is to produce and reestablish an actual array of pixels to represent objects and to enhance raw images from direct measurements. The content herein of the research is focused on one critical aspect of segmentation using K-means clustering technology. Other methodologies include smoothing, autocorrelation, wavelet method, region and edge based segmentation, and so on, can be integrated. It is expected that most significant methods for large-scale image data retrieval and segmentation can be exploited. Its future goal will be on real time image processing.

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