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A Review on Segmentation Techniques in Large-Scale Remote Sensing Images

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***Abstract*— Information extraction is a very challenging task because remote sensing images are very complicated and can be influenced by many factors. The information we can derive from a remote sensing image mostly depends on the image segmentation results. Image segmentation is an important processing step in most image, video and computer vision applications. Extensive research has been done in creating many different approaches and algorithms for image segmentation. Labeling different parts of the image has been a challenging aspect of image processing. Segmentation is considered as one of the main steps in image processing. It divides a digital image into multiple regions in order to analyze them. It is also used to distinguish different objects in the image. Several image segmentation techniques have been developed by the researchers in order to make images smooth and easy to evaluate. Various algorithms for automating the segmentation process have been proposed, tested and evaluated to find the most ideal algorithm to be used for different types of images. In this paper a review of basic image segmentation techniques of satellite images is presented.**

***Keywords*—** Remote Sensing Images; Image Segmentation; Geo-Referencing; Feature Extraction; Classification;

I. INTRODUCTION

Remote imagery consists of photographs of Earth or other planets made by means of artificial satellites. Remote images have many applications in agriculture, geology, forestry, biodiversity conservation, regional planning, education, intelligence and warfare. Images can be in visible colors and in other spectra. The applications of the high resolution Remote Sensing (RS) image processing mainly include the following aspects: city remote sensing, basic geographic mapping, environmental monitoring and assessment, precision agriculture, and public information service, etc [1]. The goal of the RS applications is to extract information and identify interested targets to complete image understanding.

Thus in general, any image can be described by a two-dimension function f_(x, y), where (x, y) denotes the spatial coordinate and f_(x, y) the feature value at (x, y). Depending on the type of image, the feature value could be light intensity, depth, intensity of radio wave or temperature. A digital image, on the other hand, is a two-dimensional discrete function f(x, y) which has been digitized both in spatial coordinates and magnitude of feature value. We shall view a digital image as a two-dimensional matrix whose row and column indices identify a point, called a pixel, in the image and the corresponding matrix element value identifies the feature intensity level. Throughout our discussion a digital image will be represented as

$$FP\times Q = [f(x, y]\ P\times Q$$

Where $P \times Q$ is the size of the image and $f(x, y) \in GL = \{0, 1, . . ., L - 1\}$,the set of discrete levels of the feature value. Since the techniques we are going to discuss in this article are developed for ordinary intensity images, in our subsequent discussion, we shall usually refer to f(x, y) as gray value (although it could be depth or temperature or intensity of radio wave). Segmentation is first essential and important step of low level vision [2].

Its application area varies from the detection of cancerous cells to the identification of an airport from remote sensing data, etc. In all these areas, the quality of the final output depends largely on the quality of the segmented output. Segmentation is a process of partitioning image into some non-intersecting regions such that each regions is homogeneous and union of no two adjacent regions is homogeneous, as shown in Figure 1.

Remote sensing image is a quite interesting application, as it is a composition of many bands, layers and objects, thus increasing the probability of image noise. Therefore, it is more difficult to extract objects, especially small objects, from remote sensing images. Image segmentation mainly includes several types, such as traditional histogram threshold method, region-based approach, edge detection, clustering in feature space and neural network method etc .With an extensive application of remote imagery especially for land resources survey, efficient methods for remote sensing imagery analysis and interpretation is a great demand. A large amount of efforts in the past have made, and some effective methods have proposed, from traditional pixel-based statistical classification methods like maximum likelihood (ML), K-Means, to popular object-oriented classification strategy[3].

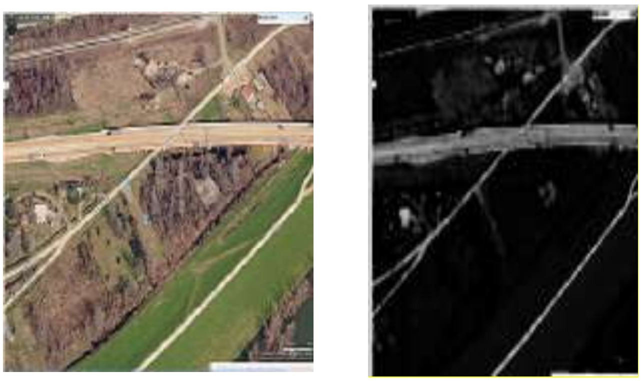

Figure 1: Image Segmentation in Remote Sensing Images

II. IMAGE SEGMENTATION TECHNIQUES

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 after the level of detail required to identify those elements is achieved [4].

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. For this reason, considerable care should be taken to improve the probability of rugged segmentation. In some situations, such as industrial inspection applications, at least some measure of control over the environment is possible at times. The experienced image processing system designer invariably pays considerable attention to such opportunities.

In other applications, such as autonomous target acquisition, the system designer has no control of the environment. Then the usual approach is to focus on selecting the types of sensors most likely to enhance the objects of interest while diminishing the contribution of irrelevant image details. A good example is the use of infrared imaging by the military to detect objects with strong heat signatures, such as equipment and troops in motion.

Image (light intensity) segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into region that are similar according to set of predefined criteria. Thresholding, pixel classification, region growing, and region splitting and merging are examples of methods in this category [2,5]. These are described in the following sections.

A. Gray Level Thresholding

Thresholding is one of the old, simple and popular techniques for image segmentation. Thresholding can be done based on global information (e.g., gray level histogram of the entire image) or it can be done using local information (e.g., co-occurrence matrix) of the image. Taxt et al. [3] refer to the local and global information based techniques as contextual and non-contextual methods, respectively. Under each of these schemes (contextual/non-contextual) if only one threshold is used for the entire image then it is called global thresholding. On the other hand, when the image is partitioned into several sub-regions and a threshold is determined for each of the sub-regions, it is referred to as local thresholding [3]. Some authors [4,5] call these local thresholding methods adaptive thresholding schemes. Thresholding techniques can also be classified as bi-level thresholding and multi-level thresholding. In bi-level thresholding the image is partitioned into two regions – object (black) and background (white). When the image is composed of several objects with different surface characteristics (for a light intensity image, objects with different coefficient of reflection, for a range image there can be objects with different depths and so on) one needs several thresholds for segmentation. This is known as multi-level thresholding.

If the image is composed of regions with different gray level ranges, i.e., the regions are distinct, the histogram of the image usually shows different peaks, each corresponding to one region and adjacent peaks are likely to be separated by a valley. For example, if the image has a distinct object on a background, the gray level histogram is likely to be bimodal with a deep valley. In this case, the bottom of the valley (T) is taken as the threshold for object background separation. Therefore, when the histogram has a (or a set of) deep valley(s), selection of threshold(s) becomes easy because it becomes a problem of detecting valleys.

Nakagawa and Rosenfeld [4] assumed that the object and background populations are distributed normally with distinct means and standard deviations. Under this assumption they selected the threshold by minimizing the total misclassification error. This method is computationally involved. Kittler and Illingworth [6], under the same assumption of normal mixture, suggested a computationally less involved method. Their method optimizes a criterion function related to average pixel classification error rate that finds out an approximate minimum error threshold. Pal and Bhandari [7] optimized the same criterion function but assumed Poisson distributions to model the gray level histogram.

B. Iterative Pixel Classification

Relaxation: Relaxation is an iterative approach to segmentation in which the classification decision about each pixel can be taken in parallel. Decisions made at neighboring points in the current iteration are then combined to make a decision in the next iteration. There are two types of relaxation: probabilistic and fuzzy.

MRF Based Approaches: There are many image segmentation methods which use the spatial interaction models like Markov Random Field (MRF) or Gibbs Random Field (GRF) to model digital images. Geman and Geman [8] have proposed a hierarchical stochastic model for the original image and developed a restoration algorithm, based on stochastic relaxation (SR) and annealing, for computing the maximum a posterior estimate of the original scene given a degraded realization.

Neural Network Based Approaches: Several authors [8-12] have attempted to segment an image using neural networks. Blanz and Gish [10] used a three-layer feed forward network for image segmentation, where the number of neurons in the input layer depends on the number of input features for each pixel and the number of neurons in the output layer is equal to the number of classes. Babaguchi et al. [9] used a multilayer network trained with back propagation, for thresholding an image. The input to the network is the histogram while the output is the desirable threshold. Ghosh et al. [12-14] used a massively connected network for extraction of objects in a noisy environment. The maximum a posterior probability estimate of a scene modeled as a GRF and corrupted by additive Gaussian noise has been done using a neural network [11]. Another robust algorithm for the extraction of objects from highly noise corrupted scenes using a Hopfleld type neural network has been developed in reference [14]. Moreover, this algorithm integrates the advantages of both fuzzy sets (decision from imprecise/incomplete knowledge) and neural networks (robustness). Kuntimad and Ranganath [15] have describes a method for segmenting digital images using pulse coupled neural networks (PCNN). The pulse coupled neuron (PCN) model used in PCNN is a modification of the cortical neuron model of Ghosh and Ghosh [16] used fuzzy logic reasoning into the Neuro-GA (Hopfield type neural network) hybrid framework where GA (Genetic Algorithm) has been used to evolve Hopfield type optimum neural network architecture for object background classification. Each chromosome of the GA represents architecture. The output status of the neurons at the converged state of the network is viewed as a fuzzy set and measure of fuzziness of this set is taken as a measure of fitness of the chromosome. The best chromosome of the final generation represents the optimum network configuration. Jiang and Zhou [17] described an image segmentation method based on ensemble of SOM (self-organized map) neural networks. This clusters the pixels in an image according to color and spatial features using each SOM, and then combines the clustering results to give the final segmentation.

C. Edge Detection

Segmentation can also be obtained through detection of edges of various regions, which normally tries to locate points of abrupt changes in gray level intensity values. Since edges are local features, they are determined based on local information. A large variety of methods are available in the literature [3,4,18-21] for edge finding. Davis [21] classified edge detection techniques into two categories: sequential and parallel. In the sequential technique the decision whether a pixel is an edge pixel or not is dependent on the result of the detector at some previously examined pixels. On the other hand, in the parallel method the decision whether a point is an edge or not is made based on the point under consideration and some of its neighboring points.

As a result of this the operator can be applied to every point in the image simultaneously. The performance of a sequential edge detection method is dependent on the choice of an appropriate starting point and how the results of previous points influence the selection and result of the next point. There are different types of parallel differential operators such as Roberts gradient, Sobel gradient, Prewitt gradient and the Laplacian operator [3,4]. These difference operators respond to changes in gray level or average gray level. The gradient operators, not only respond to edges but also to isolated points.

D. Methods Based on Fuzzy Set Theory

Application of fuzzy sets [20] to image processing was based on the realization that many of the basic concepts in image analysis, e.g., the concept of an edge or a corner or a boundary or a relation between regions, do not lend themselves well to precise definition. A gray tone image possesses ambiguity within pixels due to the possible multi-valued levels of brightness in the image. This indeterminacy is due to inherent vagueness rather than randomness. Grayness ambiguity means “indefiniteness” in deciding whether a pixel is white or black. Spatial ambiguity refers to “indefiniteness” in the shape and geometry of a region within the image.

Fuzzy Thresholding: Different histogram thresholding techniques in providing both fuzzy and non-fuzzy segmented versions by minimizing the grayness ambiguity (global entropy, index of fuzziness, index of crispness) and geometrical ambiguity (fuzzy compactness) of an image. The optimum membership function obtained enhances the object from background and denotes the membership values of the pixels for the fuzzy object region.

Fuzzy Clustering: The fuzzy c-means (FCM) clustering algorithm [19] has also been used in image segmentation [19]. The fuzzy c-means algorithm uses an iterative optimization of an objective function based on a weighted similarity measure between the pixels in the image and each of the c-cluster centers. A local extremum of this objective function indicates an optimal clustering of the input data.

E. Mathematical Morphology

The mathematical morphology is used as a tool for extracting image components that are useful in the representation and description of region shape, such as boundaries, skeletons and the convex hull. Morphological techniques are also used for pre or post processing of images, such as morphological filtering, thinning, and pruning. Morphological segmentation methods include boundary extraction via morphological gradients operation, region partitioning based on texture content, and size distribution of particles in an image [2]. Image segmentation using morphological watersheds now became an important research area. Segmentation by watersheds embodies many of the concepts of three approaches used in image processing (i.e., detection of discontinuities, thresholding and region processing) and often produces more stable segmentation results, including continuous segmentation boundaries. This approach also provides a simple framework for incorporating knowledge-based constraints in the segmentation process.

F. Wavelet Based Segmentation

Wavelets are commonly used as a tool for coding and compression. Wavelets and multi-resolution analysis together form a field which is explored for image segmentation [2]. Acharyya et al. [22] explained a scheme for segmentation of multi-texture images. The methodology involves extraction of texture features using wavelet decomposition.

G. Genetic Algorithm

Genetic algorithm, being an adaptive search techniques, has been used for image segmentation. For example, Bhanu and Fonder [20] described an approach for automatic image segmentation, in which user selected sets of examples and counter-examples supply information about the specific segmentation problem. In their approach, image segmentation is guided by a genetic algorithm which learns the appropriate subset and spatial combination of a collection of discriminating functions, associated with image features. The genetic algorithm encodes discriminating functions into a functional template representation, which can be applied to the input image to produce a candidate segmentation. The performance of each candidate segmentation is evaluated within the genetic algorithm, by a comparison to two physics-based techniques for region growing and edge detection. Through the process of segmentation, evaluation, and recombination, the genetic algorithm optimizes functional template design efficiently. Results are presented on real synthetic aperture radar (SAR) imagery of varying complexity.

III. SEGMENTATION OF COLOR IMAGES

Color is a very important perceptual phenomenon related to human response to different wavelengths in the visible electromagnetic spectrum [23,24]. The image is usually described by the distribution of three color components R (red), G (green), B (blue). Color image is often also represented by three psychological qualities hue, saturation and intensity. According to Cheng et al. [23], which is more recent study on color images segmentation, there are two critical issues for color image segmentation: (1) what segmentation method should be utilized; and (2) what color space should be adopted. At present, color image segmentation methods are generally extended from monochrome segmentation approaches. Several approaches applied to color image are discussed in their article [23], which includes histogram thresholding, region based approaches, edge detection and fuzzy techniques. A combination of these approaches is often utilized for color image segmentation. Naik andMurthy [24] recently worked on the problem of edge detection in color images. They used this edge detection method for object recognition [25], having the knowledge of the appearance of the objects from different viewpoints. Appearance of each view of the object is encoded using the descriptions of the regions involving multiple segments on the image surface.

IV. REMOTE SENSING IMAGES: METHODOLOGY

Remotely sensed image data of the earth's surface acquired from either aircraft or spacecraft platforms is readily available in digital format; spatially the data is composed of discrete picture elements or pixels and radiometrically it is quantized into discrete brightness levels. Even the data that is not recorded in digital form initially can be converted into discrete data by the use of digitizing equipments. The great advantage of having data available digitally is that it can be processed by computer either for machine assisted information extraction or for enhancement before an image product is formed [26]. Figure 2 shows the methodology involved in performing image segmentation in remote sensing images.

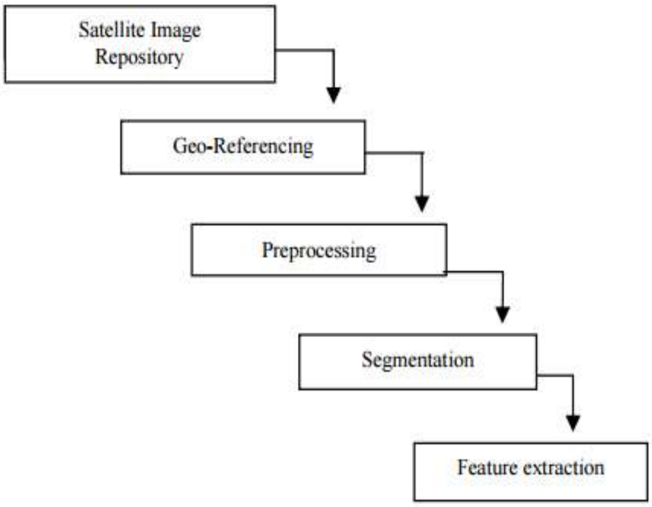

Figure 2 : Methodology for Segmentation of Remote Sensing Images

Geo-Referencing: After obtaining satellite images in the digital format, images are Geo referenced and mosaiced. Geo-referencing attaches real world coordinates to the image so that it can be co-registered with any other imagery or spatial data that overlie the same area. Geo-referencing also enables warping an image to correct the topographic displacement.

Preprocessing: Once the required data is selected, preprocessing operation is applied. Image is in RGB format, which is noisy and inconsistent. In this step, contrast level is enhanced in natural images which offers the advantage of full automation and results in higher efficiency of final results [27-28]. The image consists of an equal number of pixels for every gray-scale value which increases the sharpness and smoothness of the image to improve the clarity.

Segmentation: Image segmentation is widely used in remote sensing image since the available is of very high resolution imagery. Image segmentation often used to partition an image into separate regions, which ideally correspond to different real world objects. Efficient image segmentation is one of the most critical tasks in automatic image processing. Image segmentation has been interpreted differently for different applications. In remote sensing, it is often viewed as an aid to landscape change detection and land use/cover classification. With the numerous recent developments of new segmentation methodologies, the requirement of their categorizations based on successful applications have become essential. A variety segmentation method of evaluation methods have been used to compare the segmentation methods.

V. CONCLUSION

In this paper, we discuss and evaluate main image segmentation techniques used for the purpose of remote image analysis. It is found that there is no perfect method for image segmentation because the result of image segmentation is depends on many factors, i.e., pixel color, texture, intensity, similarity of images, image content, and problem domain. If segmentation result is good then it will result in good classification model. Along with the feature rich segmentation, time complexity and signal to noise ratios are also very important factors that have to be evaluated to determine the overall fitness of an algorithm. Therefore, it is not possible to consider a single method for all type of images nor all methods can perform well for a particular type of image. Hence, it is good to use hybrid solution consists of multiple methods for image segmentation problem.

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