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SAR Image Segmentation using Superpixel Merging Algorithm

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***Abstract*-Image segmentation is an important tool in satellite image processing and serves as an efficient front end to sophisticated algorithm and thereby simplify subsequent processing. It used to extract the meaningful objects lying in the image. The aim of the paper is to obtain the segmentation of the Synthetic Aperture Radar (SAR) image with minimum run time of the algorithm. The algorithm used for the segmentation is named as superpixel merging algorithm. In this paper instead of a pixel, the superpixels are used as basic operation units. The preprocessing stage consists of formation of superpixel. The superpixel merging algorithm is used to merge the superpixel based on the analysis of superpixel. In this edge detection, feature extraction is obtained from the final segmented output. It will use less running time for the superpixels which are not present at the boundaries of different patterns of the image. The proposed algorithm is effectively reducing the process of segmentation and computational complexity.**

Keywords-Synthetic aperture radar (SAR), feature extraction, Superpixel Merging , image segmentation

I. INTRODUCTION

Satellite Image analysis has been the vital area of research for many years. Mainly, segmentation and classification of land area are used to extract features from the image. Segmentation is a preprocessing step in SAR image analysis. Segmentation is the process of partition a digital image into number of segments. The aim of segmentation is to make simple and change, the identification of an image into meaningful and easier to analyze. Image segmentation is majorly used to identify the boundaries and objects in given SAR images. More importantly, image segmentation is the process of labeling each pixel in an image such that pixels with the unique label share me characteristics. The meaning of Context is the information about the area which are given by a single pixel, and that single pixel will give the information of the surrounding pixel also.

The result of segmentation is the set of segments that consist of the important detail of that image, or a set of contours extracted from the image. Generally the pixels of a particular region have the same characteristic like texture, colour and intensity. SAR images are differentiating the place by roughness and moisture level, which result in differences in brightness and textures. Pixel based segmentation is not applicable for the SAR image because the density of the image is high and the speckle noise in them also high. Therefore the region based segmentation is used to reduce the noise level and to reduce the computation cost of the algorithm. Remote sensing satellite images have significant applications in areas such as climate studies, assessment of forest resources, identifying urban, non-urban regions, examining marine environments. Image segmentation plays an important role in remote sensing satellite image processing. The SAR image segmentation is broadly classified as.

A. *The Methods Emphasizing Image Features*

Because speckle noises in SAR images lead to random changes in the brightness of pixels, it is often invalid to directly apply traditional segmentation methods to SAR images. Therefore, many researchers pay much attention to extracting efficient SAR image features which include the brightness after denoising, texture, edge, and hybrid features.

B. *The Methods Emphasizing Segmentation Algorithms*

Many algorithms from different mechanisms have been applied to SAR image segmentation, and they include threshold methods, clustering algorithms, statistic-model-based methods, artificial intelligence methods, support vector machine, region growing methods and so on.

Different methods of segmentation for SAR image are followed as, Image thresholding methods are popular because of their efficiency and simplicity. The traditional histogram-based thresholding algorithms cannot separate those areas which have the same gray level, but do not belong to the same part. Moreover, they cannot analysis images whose histograms are nearly a unique modal, especially when targeted region is smaller when compared with the background region. The template matching method is simple in principle, but the design of the template needs mathematical equations. A clustering method, viewing an image as a set of multidimensional data and classifying the SAR image into different land cover, according to certain homogeneity property, can get much better results of segmentation. Edge detection method is the widely used approach to problem solving in image segmentation. Detection of edges is taken place based on abrupt changes in intensity of gray levels. The performance of the algorithm will reduce when images have too many edges, and it is difficult to identify a closed curve. Region growing algorithms deal with spatial repartition of the image feature information. In general, they perform better than the thresholding approaches for several sets of images.

However, the typical region growing processes are inherently sequential. The regions produced depend both on the order in which pixels are scanned and on the value of pixels which are first scanned and gathered to define each new segment. These algorithms have proved to be successful in many applications, but none of them are good for all images or all applications. In SAR images, a pixel belongs to an area of the land space, which may not necessarily be a single land cover type. This makes the segmentation more complex and uncertainty in the result. The edge penalty Triplet .Markov Random Field reduces the noise to some extent only. Markov Random Field method as high segmentation accuracy and also computational time. The MPM (Malhotra, Pramod Kumar, Maheshwari) algorithm are not efficient for homogenous and small size images. While the RJMCMC(Reversible-jump Markov-chain. Monte-Carlo) has the segmentation accuracy of 98.28%, but the efficiency is reduced if the noise in the image is increased. The pixel based segmentation is good for edge detection, but the SAR image is of high density images, therefore this technique will be slow for computing. Therefore region based segmentation is well suited for SAR image segmentation.

In this paper, we focus on a strategy which belongs region growing/merging techniques. In region merging, regions are sets of pixels with homogeneous properties and they are iteratively grown by combining smaller regions or pixels, superpixel being elementary regions. Region growing and merging techniques use the statistical test to decide the merging of regions. A merging predicate uses this test, and builds the segmentation on the basis of local decisions.

The remainder of this paper is organized as follows. The flow chart of proposed algorithm is presented in Section II. Section III introduces problem formulation and describes the preprocessing method to obtain superpixels. Section IV Makes an analysis of superpixel context. Result and discussion in Section V. Conclusion and future work comprises in Section VI.

II. PROPOSED WORK

The algorithm will follow the steps for performing the segmentation of SAR image.

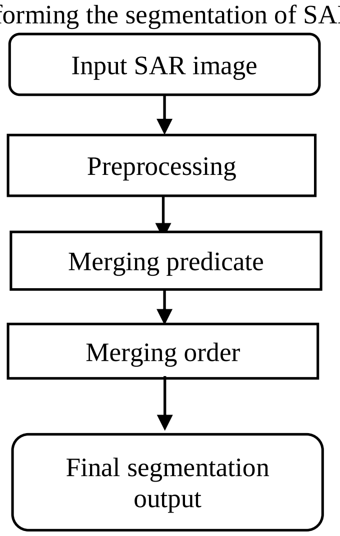

Figure 1. Overall Block Diagram

The flowchart of the region merging algorithm is shown in Figure 1, which consist of following steps. First step is the formation of superpixels and then merging of superpixel based on the statistical region merging algorithm. The superpixel context can accurately describe the contextual relationship between superpixels and further decide the labels of superpixels in the final segmentation. The segmented output is obtained in the final merging process. The Gestalt movement in psychology that perceptual grouping plays a fundamental role in human perception. Even though this observation is followed in the early part of the twentyth century, the adaptation and automation of the segmentation (and, more generally, grouping) task with computers has remained so far a tantalizing and central problem for image processing.

III. PREPROCESSING STAGE

Normally the pixels are the basic operational unit in the existing process, but in proposed algorithm the Superpixels are the basic operational units. The pixel is combined, based on the location, intensity, edges, texture and they form the superpixel. The pixel in the superpixel will have the same brightness. Superpixel may reduce the speckle noise and help to increase the speed of the algorithm. For example, if brightness are chosen as the constraint, in this paper, a level-set method called TurboPixels [6] is chosen as the preprocessing method to produce superpixels. In TurboPixels, a user-specified number of seeds are first distributed uniformly over the image plane, and then, the seeds keep dilating to approach the local image structures. During the dilating process, a Gaussian-smoothing filter is first performed to suppress noise, and then, the gradient of image edges and the curvature of seeds' boundary are taken into the seeds' evolution equation. Since superpixels can reduce the influence of speckle noises, preserve most edges of images, and are approximately uniform in size and shape, they are utilized as the basic operation units in this paper. The superpixels of SAR images produced by TurboPixels [6] are shown in Figure.2 (b), (e). At the preprocessing step, the input SAR image is oversegmented into Ns superpixels. The proposed algorithm will next merge the superpixels based on the analysis of superpixel context.

IV. ANALYSIS OF SUPERPIXELS

In region merging, regions are sets of pixels with similar characteristics and they are iteratively grown by combining smaller regions or superpixel. Region merging techniques use the statistical test to decide the merging of regions. A merging predicate and an order to test region mergings, are used to define our merging process in the SAR image segmentation. Considering that a region is an unordered bag of pixels (i.e. superpixel). The clear definition of the merging will be given in the following way. Let I denote an image and H gives a certain homogeneity predicate. The segmentation of I is a segment S of I into a set of N regions R1, R2, RN, such that [11].

$$\bigcup_{N=1}^{N} \mathrm{Rn} = \mathrm{I} \text{ with } \mathrm{Rn} \cap \mathrm{Rm} = \Phi \,,\, \mathrm{n} \neq \mathrm{m} \tag{1}$$

$$\mathrm{H(Rn)} = \text{true } \forall \mathrm{n}; \tag{2}$$

$$\mathrm{H(Rn} \cup \mathrm{Rm}) = \text{false } \forall \mathrm{Rn} \text{ and } \mathrm{Rm} \text{ adjacent.} \tag{3}$$

For our segmentation, we use the Superpixel Merging algorithm that belongs to the region growing method, in which area test are performed for region fusion.

A. *Merging predicate*

For do N, merging tests in the image I. Then, the couples of regions (S_P, S_P') whose merging is tested shall satisfy the$\left|\left(\overline{S_P} - \overline{S_P'}\right) - E\left(\overline{S_P} - \overline{S_P}'\right)\right| \leq b(S_P, S_P')$. In 4-connexity they will be N <2|I|. The merging of two observed regions S_P and S_P' is a predicate accurate enough when the pixels of S_P U S_P' come from the same statistical region of I*. In this case, E($\overline{S_P} - \overline{S_P'}$) =0 and, thus, with high probability, the deviation |$\overline{S_P} - \overline{S_P'}$ |does not exceed $b(S_P, S_P')$.

Such a predicate is optimistic under some assumption, sometimes it may lead to overmerging operation (i.e., it does more merges than necessary to actually recover I*), but this phenomenon formally remains quantitatively small. For both theoretical and practical considerations, are done by replacing the merging predicate with a larger merging threshold.

I is a colour image with |I| pixels, each one consist of three values (R, G, B) belonging to the set {1, 2... g}. The model considers image I as an observation of perfect unknown scene I* in which pixels are denoted as a family of distributions from which every colour level is sampled. In particular, every colour level of each pixel of I* is described by a set of Q independent random variables with values in [0, g/Q]. In I* the optimal regions satisfy the following homogeneity properties as given by Nielsen and Nock [14].

- Inside any statistical region and for any color channel, statistical pixels have the same expected value for this colour channel.
- The expectation value of adjacent regions is different for at least one colour channel, S_Pa denotes the observed average for color a region on S_P whereas S_P|I| is the set of regions with l pixels.

$$P(S_P, S_P') = \begin{cases} TRUE & if\ V_a \in \{R, G, B\}, \left|\overline{S_P}'a - \bar{s_p}a\right| \leq b(s_p) + b(s_p') \\ FALSE & otherwise \end{cases} \tag{4}$$

$$\mathrm{b(s_p)} = \mathrm{g}\sqrt{\frac{1}{2\mathrm{q}\,|\,\mathrm{s_p}\,|}\left(\ln \frac{|\,\mathrm{s_{P|R|}}\,|}{\delta}\right)} \tag{5}$$

$$b(s_p, s_p') \leq \sqrt{b^2(s_p) + b^2(s_p') < b(s_p) + b(s_p')} \tag{6}$$

$S_P{}' a$ denotes the observed average for color an in region of S_P whereas $S_{P|l|}$ is the set of regions with l pixels.

B. Merging order

Ideally, the order to test the merging of regions is, when any testing takes place between any of two true regions, then all tests in each of the two true regions have previously performed in the merging predicate itself. Order of merging is choosing a real-valued function f and radix sort f (. , .) to approximate the order in merging. The order in which the tests of merging were done follows a simple invariant A.

In the experiments, A is approximated by a simple algorithm based on gradients of near pixels. In particular, Nielsen and Nock [14] consider a function f defined as follows:

$$f(p, p') = \max_{a \in R,G,B} f_a(p, p') \tag{7}$$

$$f_a(p, p') = | p_a - p'_a | \tag{8}$$

For more critical function, that extends classical edge detection convolution kernels could be used to define fa. The Sobel gradient mask is used for detecting the edges. The set of the pairs of adjacent pixel (S_PI) is sorted according to the value of (4). Afterwards the algorithm takes every couple of pixels (p, p') of SI and if the regions to which they belong (S_P(p) and S_P(p')) were not the same and satisfactory (1), it merges the two regions.

V. Results And Discussion

The algorithm suffers only one source of error for image segmentation is overmerging, that is, the fact that some observed region may contain more than one true region. The algorithm does not suffer neither undermerging, nor the hybrid cases were observed regions may partially have several true regions. In our algorithm scale is controlled by tuning of parameter Q. When the value of Q is increased, the regions found are getting smaller and vice versa. The algorithm had increased the speed and decreasing cost of computation, the preprocessing is performed for the input images which is on Ku-band SAR image of the area of the China Lake Airport.

The required number of superpixel are obtained from the preprocessing stage. The output image of preprocessing is then used for the contextual analysis. The final segmented output is obtained in the superpixel merging stage by using the merging predicates and merging order. The accuracy of the final segmentation result is mainly decided by merging predicates. The edges are extracted from the input image. The preprocessing stage will be similar for CHMUSIS and the proposed method. The experiments are conducted on a machine of Intel I5 with 2.4 GHz and 4-GB memory and an operating system of Window 7, with Matlab version 8.1.0.604.

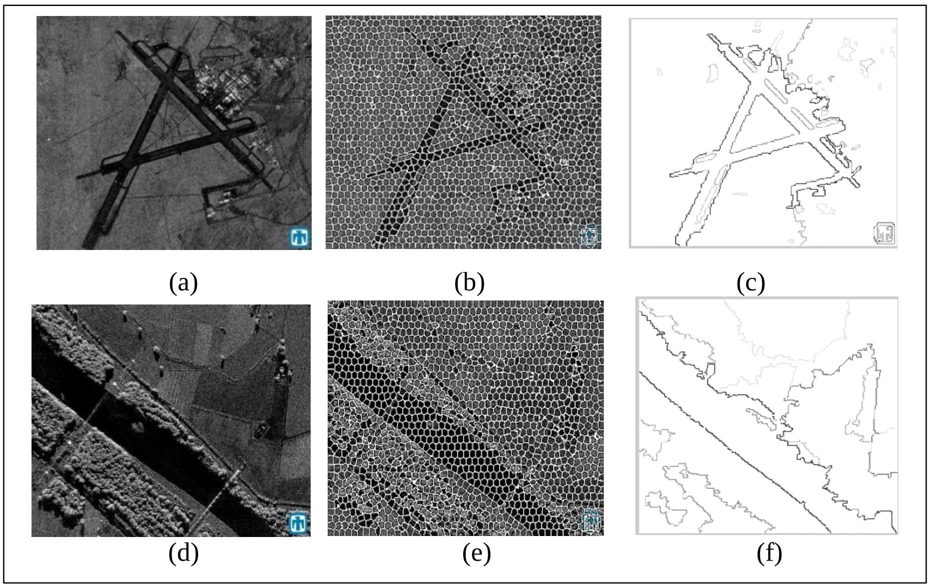

Figure 2. (a) & (d) is the input SAR Image of China Lake airport and Rio Grande River
(b) & (e) Superpixels formed from input images (c) & (f) Final segmentation output.

TABLE 1: COMPARISON TABLE FOR COMPUTATION TIME OF DIFFERENT SAR IMAGES

Input image	Computation time (sec)					
	CHUMSIS			**Proposed method**		
	Preprocessing	Merging stage	Total time	Preprocessing	Merging stage	Total time
Chinalake airport (522X446)	20.45	23.31	43.76	20.45	7.637	28.09
Piperiver (600X432)	28.23	24.48	56.71	28.23	8.626	36.86
Image of unions(995X1050	32.99	45.41	78.40	32.99	27.47	66.46

VI. Conclusion

This Merging algorithm adopts superpixels as the operating unit. The merging strategy in this method makes a minimum computation time for segmenting the SAR image. From the results (Table 1), the computation time is directly proportional to the size of the image. The final segmented output gives the edges of the objects, present in the input image. There are still some problems: 1) The accuracy of superpixels produced by the preprocessing step will also influence the final segmentation and 2) Algorithm suffers only one source of error for image segmentation which is of overmerging of superpixel, which can reduce the algorithm's speed. These problems will be our future work.

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