Iterative SAR Segmentation by Fuzzy Hit-or-Miss and Homogeneity Index

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Abstract — **Object-based segmentation is the first essential step for image processing applications. Recently, SAR (Synthetic Aperture Radar) segmentation techniques have been developed, however not enough to preserve the significant information contained in the small regions of the images. The proposed method is to partition an SAR image into homogeneous regions by using a fuzzy hit-or-miss operator with an inherent spatial transformation, which endows to preserve the small regions. In our algorithm, an iterative segmentation technique is formulated as a consequential process. Then, each time in iterating, hypothesis testing is used to evaluate the quality of the segmented regions with a homogeneity index. The segmentation algorithm is unsupervised and employed few parameters, most of which can be calculated from the input data. This comparative study indicates that the new iterative segmentation algorithm provides acceptable results as seen in the tested examples of satellite images.**

I. INTRODUCTION

Image segmentation is an important first step for many processing applications. With applications ranging widely from remote sensing to medical image analysis, segmentation is often a key step for extracting information from images. Segmentation is a process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of two any adjacent regions is not homogeneous [1].

The peculiar segmentation of satellite images requires automated or semi-automated analysis because the satellite images have huge volumes of data and detailed information. In this paper, a single pertinent algorithm capable of handling many situations in satellite image segmentation is designed to preserve detailed information and to partition images accurately. The homogeneity index and the fuzzy hit-or-miss operator are employed in the iterative segmentation process to partition the images until all regions met an acceptable level of homogeneity. The homogeneity index is a standardized measurement designed to estimate the quality of the segmented regions [2]. The fuzzy hit-or-miss is an operator in a fuzzy mathematical morphology [3-8]. For the segmentation results, the proposed scheme has been applied and tested successfully with detailed information from JERS-1 and ERS-1, which are SAR images containing corrupted speckle noise.

II. FUZZY MATHEMATICAL MORPHOLOGY

The generalization of the binary morphological operators to grey scale is achieved by several techniques, e.g., the umbra approach [14] and the threshold decomposition in the soft morphological technique [15]. A fuzzy set is also one of these techniques. A basic idea of performing the image processing with the fuzzy set and grey-scale morphology is to define the effective operations. This process represents grey-scale imaging by the fuzzy set and, it employs fuzzy tools according to grey-scale morphology. Therefore, fuzzy set and mathematical morphology are incorporated in the form of "fuzzy mathematical morphology."

Fuzzy mathematical morphology was proposed in several approaches, e.g., an approach based on Minkowski [3], on the fuzzification of set inclusion [4-6] and on weighted order statistics [7]. From a comparative study of Bloch et al. [8] and our experimentations in image thresholding [9], edge detection [10], segmentation [11] and enhancement [12], the fuzzy inclusion provides a satisfactory technique. In addition, fuzzy inclusion can be used to formulate two-argument operators [13] to express the fuzzy set relation and to measure a subset-hood of a possibility in the proposition "$A\subset B$". The elementary operators of the fuzzy mathematical morphology by the fuzzy set inclusion, which consist of erosion and dilation, use fuzzy structuring elements. These are defined in equations (1) and (2), respectively,

$$\mu_{f\ominus k}(z) = I(T(k;v), f(z)) \tag{1}$$

$$\mu_{f\oplus k}(z) = \mu_{(f'\ominus(-k))'}(z) \tag{2}$$

where $\mu_{f\ominus k}$ and $\mu_{f\oplus k}$ denote the membership values of the fuzzy erosion and fuzzy dilation, respectively; $z = xN+y$ (with an image size of $M\times N$). The spatial translation, $T(k;v)$, of the structuring element k by v is expressed as

$$\mu_{T(k;v)}(z) = \mu_k(z-v) \tag{3}$$

where v denotes the coordinate of k. The degree of the subset-hood is estimated in terms of an indicator function, $I(T(k;v),f(z))$. The satisfaction indicator fitting the characterization of fuzzy morphological operations according to the fuzzy inclusion [4] was given by

$$I(k,f) = \inf_{z\in M\times N} \min[1, \lambda(\mu_f(z)) + \lambda(1-\mu_{T(k,v)}(z))]. \tag{4}$$

This equation applies an infimum (inf) operator to the values of fuzzy set k of the membership functions, which belong to the subset of the image, f. Sinha et al. [4] proposed a family of λ-functions corresponding to the indicator function that had been used in various applications [5]. In our segmentation of grey-level images, the optimal λ-function based on our experimentations is employed and defined as

$$\lambda_n(w) = \frac{1}{1+w^n} - \frac{w}{2}; \quad n \geq \frac{\ln(3)}{\ln(2)} = 1.5849... \quad (5)$$

where w of the λ-function's argument represents the *membership values* of the images and structuring elements.

In the proposed method, segmentation process of the SAR images is performed by the fuzzy hit-or-miss operator, which is expressed in Eq. (6). This operator detects the homogeneous regions by fitting the object areas with the structuring element k_1, and fitting the background region by the structuring element k_2, where k_1 and k_2 are fuzzy sets.

$$\mu_{f\otimes(k_1,k_2)} = \mu_{f\ominus k_1} \cap \mu_{f^c\ominus k_2} \quad (6)$$

An object in the foreground is detected and mapped to the range (0,1] by the fuzzy hit-or-miss operator and in the background is mapped approaching to zero. In grey-scale morphology, note that, $k_1 \cap k_2 \neq \emptyset$. By the properties of a hit-or-miss transformation, the "hit geometrical investigation," k_1, establishes a fit to the brightness levels (in term of membership function, $\mu_f(x, y)$) of foreground images to the object sets. The "miss structuring element," k_2, representing the background regions, provides the fitting for the darkness levels of the background images. The intersection term in hit-or-miss applies to a decision-maker that assigns a pixel in each region to the objects or the backgrounds.

III. Homogeneity Index

An image consists entirely of regions that are homogeneous. Adjacent regions are separated by boundaries corresponding to changes in local statistics, such as brightness average or texture variables. The segmentation methods recover these regions from the local statistics that are usually the expected values. The proposed method uses the homogeneity index, U, to measure the former by dividing an input image with the segmentation algorithm. The homogeneity index is given by integrating the normalized intra-region uniformity values [2]. The uniformity of a feature over a region can be computed on the basis of the variance of that feature evaluated at every pixel belonging to that region. In particular, for a grey-level image $f(x, y)$, let R_i be the i^{th} segmented region, A_i be the area of R_i, and U be the normalized intra-region uniformity of the L classes,

$$U = 1 - \frac{\sum_{i=1}^{L} \sum_{(x,y)\in R_i} \left(f(x,y) - \frac{1}{A_i} \sum_{(x,y)\in R_i} f(x,y) \right)^2}{C} \quad (7)$$

where C denotes the normalization factor. In the proposed scheme, factor C is obtained from the variance of the picture. The term $\frac{1}{A_i} \sum_{(x,y)\in R_i} f(x,y)$ is the expected value of the i^{th} region from the segmentation methods. If all the regions are homogeneous, then the expected values and variances of the homogeneity index, U, are easily interpreted as the nearer U is to 1, the better the homogeneity within classes.

IV. Methodology

In this section, an automatic iterative segmentation algorithm to partition a SAR image into the homogeneous regions is described. The algorithm is unsupervised and employed a number of parameters, most of which can be calculated from the input images. The segmentation algorithm consists of two major steps: segmentation and homogeneity measuring. In the segmentation step, the fuzzy hit-or-miss operator is applied to segment grey scale images in the spatial domain. This step consists of three routines, namely (i) fuzzifying the input images, (ii) identifying the structuring elements and (iii) segmenting the image regions. The homogeneous measuring step computes the homogeneity index (U in Eq. (7)) from the segmented regions and uses U to compare with the *Homogeneity* value. If U is less than the *Homogeneity* value, it means that some regions in the images are non-homogeneous; consequently, the segmentation step is called again (iterative mechanism). Conversely, if U is more than the *Homogeneity* value, it indicates that the segmented regions are homogeneous. If so, then the automatic algorithm is finished.

A. Algorithm Parameters

Since the proposed algorithm is the unsupervised and automatic processing, the parameters are formulated depending on the input images. From our experimentations with 100 sample images, these parameters have two groups: constant and varying. The algorithm has two constant parameters, the parameter n (=2.75) of the λ-function and the *Homogeneity* (=0.95) value, which is defined with a significant level of 5%. The homogeneity index is taken into consideration as a proportion variable of the homogeneous regions, which is the statistic values estimated from the segmented regions; then, the comparison in this case can be considered as hypothesis testing. Therefore, the *Homogeneity* value is taken into account of the proportion parameter for rejecting the null hypothesis, which is defined as "the segmented results are homogeneous."

The varying parameters are computed directly from input images. These parameters are employed to fuzzify an input image and to characterize a structuring element. In the fuzzifying process, the varying parameters: a, b, and c, contain in the fuzzification function are given by

$$\mu_f(x,y) = S(f(x,y),a,b,c)$$
$$= \begin{cases} 0, & lMin \leq f(x,y) \leq a \\ 2\times\left(\frac{f(x,y)-a}{c-a}\right)^2, & a < f(x,y) \leq b \\ 1-2\times\left(\frac{f(x,y)-c}{c-a}\right)^2, & b < f(x,y) \leq c \\ 1, & c < f(x,y) \leq lMax \end{cases} \quad (8)$$

where parameters a, b and c are provided by **Algorithm 1** in [10], $lMin$ and $lMax$ stand for minimum and maximum of pixel values, respectively. Term sets of "object" and "background" are given by the S-function and $1-S(f(x, y), a, b, c)$ or S^{-1}, respectively.

The parameters of structuring elements have a high sensitivity for extracting the important features. These parameters are used to separate the object pixels from background pixels. From the experimentations, the values for the structuring elements are given in 3×3 windows. Fig. 1 shows patterns of the structuring elements k_1 and k_2 which are employed the fuzzy hit-or-miss operator.

$$k_1 = \begin{bmatrix} 0 & h & 0 \\ h & h & h \\ 0 & h & 0 \end{bmatrix}, \qquad k_2 = \begin{bmatrix} 0 & m & 0 \\ m & m & m \\ 0 & m & 0 \end{bmatrix}$$

Fig. 1. The structuring elements, k_1 and k_2, with 3×3.

The parameters h and m in the structuring elements k_1 and k_2 have been given according to input data, and correspond to the average values of object and background regions. Both the "hit", h, and the "miss", m, are expressed by

$$\begin{aligned} h &= \sum_{z \in M \times N} \mu_f(z) f(z) \Big/ lMax, \\ m &= \sum_{z \in M \times N} \left(1 - \mu_f(z)\right) f(z) \Big/ lMax. \end{aligned} \tag{9}$$

B. Algorithm

The iterative algorithm designed to segment a SAR image is shown in Fig. 2. This algorithm consists of two major parts: (1) initial values as described previously in sub-section *A* and (2) iterative segmentation. Before operating with the algorithm, an input image is enhanced and removed noise with nonlinear filter as formulated by Nitzberg *et al.* [16]. For parameters of the nonlinear filter, we define the window width as (N = 7), the gradient window size as (*tau* = 1.5). The overall broadness of the blurring kernels (*sigma*) and the displacement attenuation (*mu*) parameters are defined by the mean and standard deviation of an input image.

From Fig. 2, the iterative segmentation is divided into three blocks:

(2.1) Updating segmentation parameters, which consist of fuzzifying the current labelling regions, calculating the structuring elements by Eq. (9), initializing the coordinate pixel, (x, y), and incrementing class labelling parameters, *LabelForeground* and *LabelBackground*,

(2.2) Fuzzy hit-or-miss operation, which consists of refining labelled pixels (2.2.1), getting a neighborhood of the labelled pixels into 3×3 windows and applying the fuzzy hit-or-miss operator (2.2.2), and deciding which *LabelForeground* or *LabelBackground* is assigned to labelled pixels, $g(x,y)$,

(2.3) Homogeneity measuring, which consists of calculating the homogeneity index, U by Eq. (7), comparing U with the critical level of the *Homogeneity* value, and searching the non-homogeneous regions to declare *Label* variable.

V. Experimental Results

The performance of proposed algorithm to segment SAR images is assessed with visual judgment. To evaluate the accuracy of the algorithm, the SAR images are tested by comparing with the second algorithm fuzzy C means of Jawahar et al. [17] and SAR segmentation of Zaart *et al.* [18]. In comparison process, class numbers of the fuzzy C means is defined equal to our method; meanwhile, Zaart's algorithm can calculate the number of classes from zero-crossing of the image histogram [18].

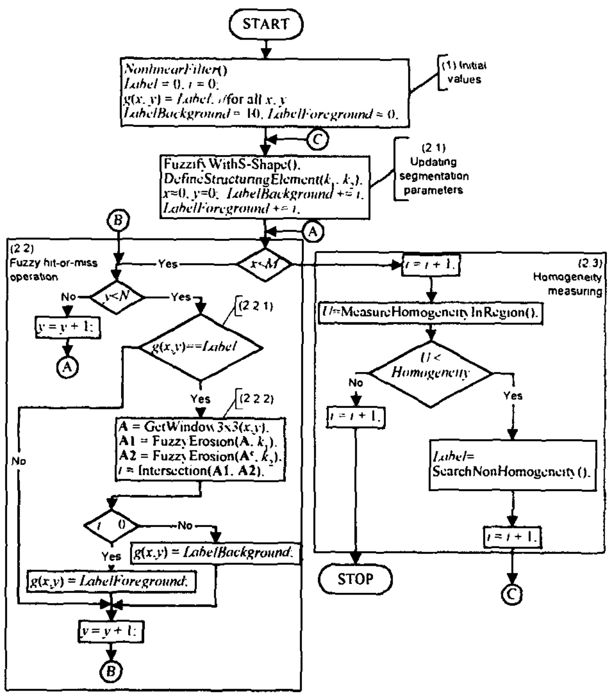

Fig. 2. The automatic iterative segmentation algorithm.

Fig. 3(a) shows the original SAR image, which is corrupted with speckle noise. It is from the satellite JERS-1 that has a resolution of 12.5 m^2 and which covers some area of Bangkok, Thailand (taken on 25 June 1992). Fig. 3(b) shows the segmented result by our method, which the result consists of 5 classes and a homogeneity index of U = 0.921396. Fig. 3(c) illustrates 5 classes of segmented result by the fuzzy C means (U = 0.819757). Fig. 3(d) shows 6 classes of segmented result of Zaart et al. (U = 0.807392), with L=1.031600 at the rectangular coordinate (83, 131, 156, 206).

Fig. 4(a) illustrates the ERS-1/AMI image, which has a resolution of 12.5 m^2 and covers some parts of Kanchanaburi province, Thailand (taken on 22 November 1991). Fig. 4(b) shows the segmented image by our method, which this image consists of 6 classes. The homogeneity index, U, of the segmented image is 0.902920. Fig. 4(c) illustrates 6 classes of segmented image, which is operated by the fuzzy C means (U = 0.903481). Fig. 4(d) shows 7 classes of segmented image, which is processed by Zaart's algorithm (U = 0.893893), with L=3.039824 at the rectangular coordinate (1, 1, 45, 93).

VI. Conclusion

The iterative segmentation algorithm presented here, has been developed and successfully implemented for

SAR images. It utilizes the effective combination of the fuzzy hit-or-miss operator and the homogeneity index.

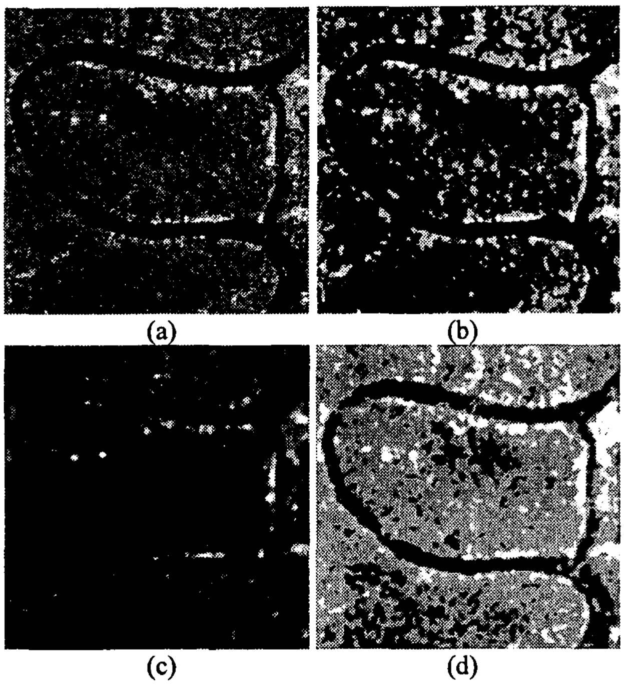

Fig. 3. The SAR image from JERS-1 that is corrupted with speckle noise, (a) the input image (256 × 256 pixels), (b) the segmented image by the proposed method, (c) processed by fuzzy C means, and (d) processed by the method of Zaart *et al.*

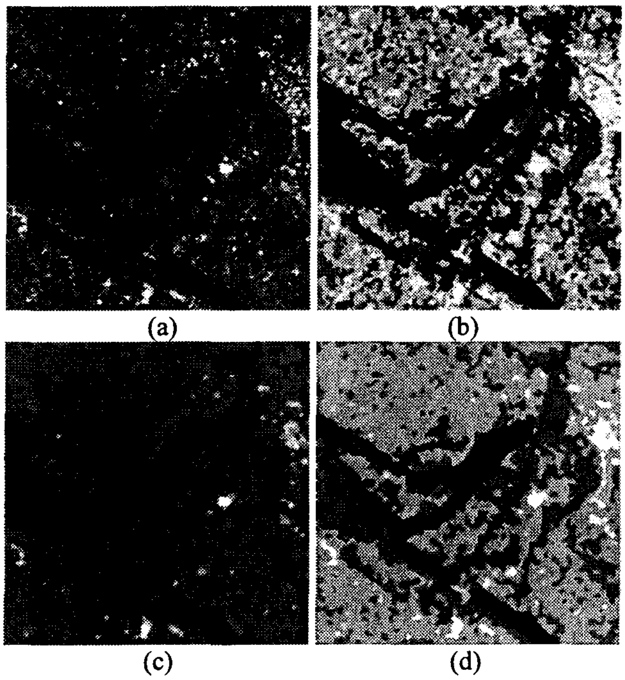

Fig. 4. The SAR image from ERS-1/AMI corrupted with speckle noise, (a) the input image (256 × 256 pixels), (b) the segmented image by the proposed method, (c) processed by fuzzy C means, and (d) processed by the method of Zaart et al.

The proposed method iteratively performs hierarchical segmentation. For each loop of segmentation processing, the fuzzy hit-or-miss operator separates the image regions into two classes (object and background); furthermore, it can estimate the class numbers in an image, which depend on the homogeneity information obtained from the homogeneity index. The higher the value of *homogeneity* is, the greater the number of classes there will be. However, the number of classes depends directly on the detail of an input image. From the experimentations, the proposed segmentation algorithm outperforms the fuzzy C means and Zaart's algorithm. Although, the proposed algorithm has the numbers of class less than Zaart's algorithm, it provides U higher than Zaart's algorithm as seen in Fig. 3 and 4. In particular, the proposed method provides a better object segmentation than the histogram-based method and it also retains small but significant regions in satellite images.

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