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Change Detection on Images Using Morphological Processing

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Abstract— ***Change detection is mainly performed on polarimetric synthetic aperture radar (PolSAR) images. In this paper, a novel method for performing change detection on any type of images is proposed. First, a heterogeneous clutter model is used for estimating parameters from the images. Then a similarity measure is used in order to obtain the difference map between images. Here, morphological processing is used for segmenting the changed areas. This process can clearly figure out each objects present in the images. Erosion is the basic morphological processing operator which is used in this paper for change detection. Erosion can effectively determine the changed regions in the images based on dark region on the binary image. This operator is produced by the interaction of a set called a structuring element with a set of pixels of interest in the image. The basic effect of this operator on a binary image is to erode away the boundaries of regions of foreground pixels (i.e., typically white pixels). The increased number of dark pixels in the difference binary map image produced from the comparison operation, indicate the changed regions in the image. This morphological image processing operator can effectively perform change detection on any type of images.***

Keywords— ***Change detection, Erosion, Morphological processing, Similarity measure, Spherically invariant random vector (SIRV) distribution models.***

I. INTRODUCTION

Change detection is a process which determines how much the attributes of a particular area have changed at two or more time intervals. Change detection often involves comparing SAR images of the area taken at different time intervals. The Synthetic Aperture Radar (SAR) is an ingenuous radar system which acquires very high resolution images of objects, for example landscape. Several features such as area, texture, shape, average intensity, and underlying land cover, can be used for performing change detection in single-channel SAR images [2] - [5].

In fully polarimetric SAR (PolSAR) systems, interactions between the electromagnetic wave and the target area with all combination of transmit and receive polarization are described [6]. In addition to this, most of the recently launched PolSAR systems also have the capability of polarimetric imaging. Both phase and amplitude information from radar returns transmitted in two different polarizations are contained in PolSAR data. Hence more scattering information can be used in the change detection of PolSAR data than the single-channel SAR data. SAR data play important role in representing information for environmental monitoring applications or disaster assessment and prevention.

In change detection of PolSAR data, an appropriate distance between the corresponding areas of multitemporal scenes should be measured using fully polarimetric heterogeneous clutter model. A commonly used heterogeneous clutter model is spherically invariant random vector (SIRV) distribution model. The SIRV is a class of nonhomogeneous Gaussian processes with random variance. It defines the target scattering vector as the product between the square root of a scalar random variable and an independent zero-mean complex circular Gaussian random vector. However, the probability density function (pdf) of the texture random variable is not explicitly specified in the SIRV definition. Hence Gamma texture distribution leads to either κ clutter distribution [9], [10] , $\mathcal{G}^0$ distribution [7] or KummerU distribution [8], which can be used in some applications of PolSAR such as image classification and segmentation and target detection.

Speckle is a granular noise that exists inherently and degrades the quality of PolSAR images. Speckle noise is generally serious causing difficulties in image interpretation and hence reduces the accuracy of PolSAR segmentation and classification. The cause of these noise is coherent processing of back scattered signals from multiple distributed targets. multilook processing is a procedure which is commonly adopted for reducing the noise effects in PolSAR images by spatial averaging. In this case, polarimetric covariance or coherency matrix is a more appropriate way for representing PolSAR data.

In this paper, morphological processing is used for segmentation so that change detection can also be applied for all kind of images in addition to SAR images. The morphology contribute a wide range of operators to image processing, all based on concepts from set theory. Here set is a collection of pixels in the images. The operators are particularly useful for analyzing binary images and common usages includes edge detection, image enhancement, noise removal and image segmentation. Morphological techniques typically perform probe on an image with a small shape or template known as a structuring element. This structuring element is positioned at all possible locations in the image for comparing it with the corresponding neighborhood pixels. Dilation and erosion are the basic morphological processing operations which are produced by the interaction of structuring elements with a set of pixels of interest in the image.

The objective of this paper is to extend change detection method to all kinds of images using SIRV clutter model and morphological processing. This paper is organized as follows. Section II describes the multilook clutter model which is introduced to fit the statistical characteristic of the coherency matrix. A similarity measure is defined for change detection based on the log-likelihood function. In Section III, an unsupervised change detection approach is developed. The similarity measure is calculated from the difference map between two temporal images. Then morphological processing is applied for segmentation.

II. SIMILARITY MEASURE

This section describes the SIRV distribution model and subsequently introduces a multilook product model to describe multilook data [1]. Then, the covariance matrix estimation method of this model is derived. Finally, based on gamma-distributed texture assumption a similarity measure is introduced for change detection of images.

A. SIRV Model

SIRV distribution model defines the target scattering vector k as the product of the square root of a scalar random variable τ (representing the texture) and an independent zero-mean complex circular Gaussian random vector z ϵ N(0,∑) with covariance matrix $\sum=E\{zz^H\}$ (representing speckle), i.e.,

$$k=\sqrt{\tau}z \tag{1}$$

where E{…} denotes the statistical mean, and H is the conjugate transpose operator. For model identification, the trace of the covariance matrix is normalized to the dimension of the target scattering vector denoted by p (p=3 for the reciprocal case).

The pdf of the target scattering vecor k is given by:

$$P_k(k;\sum)=E_\tau\{p_{k;\tau}(k|\tau;\sum)\}$$
$$= \frac{1}{\pi^p|\sum|}\int_0^{+\infty}\frac{1}{\tau^p}\exp\left(-\frac{k^H\sum^{-1}k}{\tau}\right)p_\tau(\tau)\,d\tau \tag{2}$$

where |…| denotes the matrix determinant, and $p_\tau(\tau)$ is the texture pdf.

SIRV model estimates three parameters: the covariance matrix of speckle ∑, the texture τ, and the parameters of texture pdf $p_\tau(\tau)$. With the normalized constraint on covariance matrix, the appropriate maximum likelihood (ML) estimator of ∑ is a solution of the following equation:

$$\sum^\wedge=\frac{p}{N}\sum_{i=1}^{N}\left(\frac{k_ik_i^H}{k_i^H\sum^{\wedge -1}k_i}\right) \tag{3}$$

where N is the number of pixels in the boxcar sliding neighborhood window.

For a given covariance matrix ∑, the ML estimator of the texture for pixel i is given by:

$$\tau_i^\wedge=\frac{k_i^H\sum^{\wedge -1}k_i}{p} \tag{4}$$

Based on texture distribution function when texture is obtained, the texture pdf parameters can be estimated by using an ML estimation method or a log-cumulant method [11], [12].

Similarly, let the texture be normalized; the sample covariance matrix will be the covariance matrix of speckle.

$$\sum^\wedge{}_{SCM}=\frac{1}{N}\sum_{i=1}^{N}k_ik_i^H \tag{5}$$

The above mentioned normalized texture assumption is applied to the homogeneous clutter parameter estimation. On the other hand, the normalized covariance SIRV solution in eq.(3) is suitable for the heterogeneous clutter models.

B. Similarity Measure For Change Detection

For change detection of two images, a measure needs to be defined in order to describe the similarity between their corresponding sliding windows, i.e., X and Y. Also these two sliding windows will be having same number of samples $N_X = N_Y = N$ for performing comparisons. Given the pdf of X and Y , the general form of similarity measure is defined by [13], [14], [15]:

$$S = MLL(X) + MLL(Y) - MLL(X \cup Y) \tag{6}$$

where ∪ denotes the union operator, and MLL(.) denoted the maximum log-likelihood (MLL) function. For any area Q, the expression for MLL function is :

$$MLL(Q = \sum_{i\epsilon Q}\ln(p_T(T_i\mid\theta_Q)) \tag{7}$$

where θ_Q represents the set of distribution parameters. The area where a change has occurred will give a higher similarity measure value than those that have not changed.

III. CHANGE DETECTION METHOD

Change detection method involves mainly four major steps: preprocessing filtering and co-registration, difference map extraction, threshold segmentation, and image fusion. Heterogeneous clutter models are used for estimating the statistical characteristics in images and the difference between the statistical characteristics of images are measured by the similarity measure. Once the difference map is extracted, then the morphological processing is used to extract a binary mask for change detection. Following section discuss about the filtering and segmentation processes used for change detection.

A. Filtering Process

The proposed change detection method is a pixel - to – pixel processing with a moving neighborhood window; therefore, the noise incoherent in images will effect on the accuracy of change detection process. Filters like Lee filter or boxer filter is used for removing noises in the image. However this will not only weaken the effect of noises in the image but will also degrade the statistic distribution of image data. Therefore, filtering process needs to be done only when it is required. Thus this change detection method effectively hands the problem of noises that are present in the image and hence reduce error rate in the result and increase the change detection rate.

B. Morphological Image Processing

The field of mathematical morphology contributes a wide range of operators to image processing, which are based on concepts of set theory. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological techniques typically probe an image with a small shape or template known as a structuring element [15]. The structuring element is positioned at all possible locations in the image for comparing with the corresponding neighborhood of pixels. Morphological operations differ by how they carry out these comparisons.

The structuring element is also called as kernel. The structuring element consists of a pattern specified as the coordinates of a number of discrete points relative to some origin. Usually cartesian coordinates are used for image processing and hence, a convenient way of representing the element is as a small image on a rectangular grid. The center of the structuring element is not necessarily be the origin, but often it is.

The basic morphological processing operations are dilation and erosion [16]. While either set A or B can be taken as an image, A is usually considered as the image and B is called a structuring element. In general, dilation causes objects to dilate or grow in size while erosion causes objects to shrink. The amount and the way by which they grow or shrink depend upon the choice of the structuring element. Erosion and dilation works by translating the structuring element into various points in the input image, and then examining the intersection between the translated kernel and input coordinates. For instance, in erosion, the output coordinate set consists of only those points to which the origin of the structuring element can be translated, while the element still remain entirely within the input image.

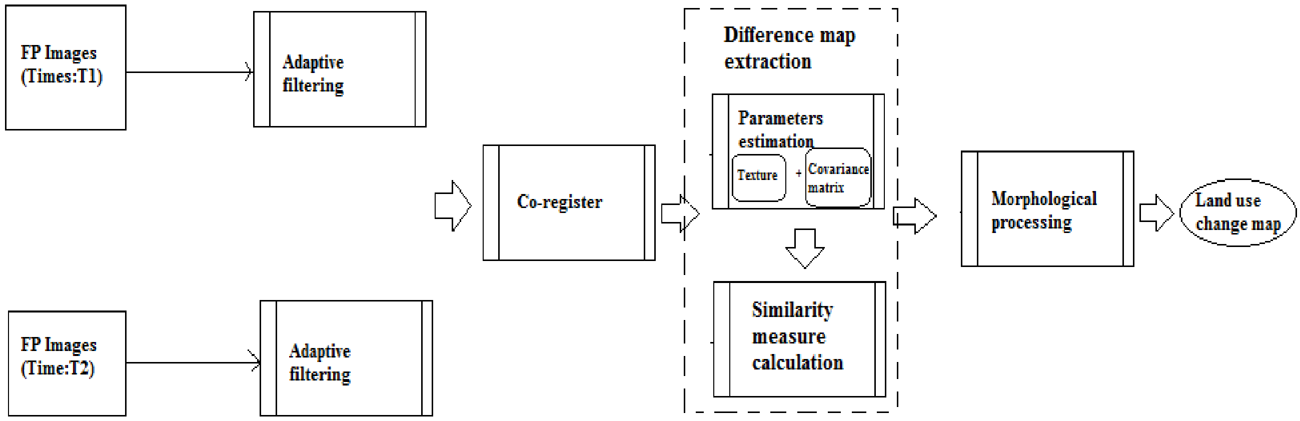

Fig.1 Flowchart of the proposed method

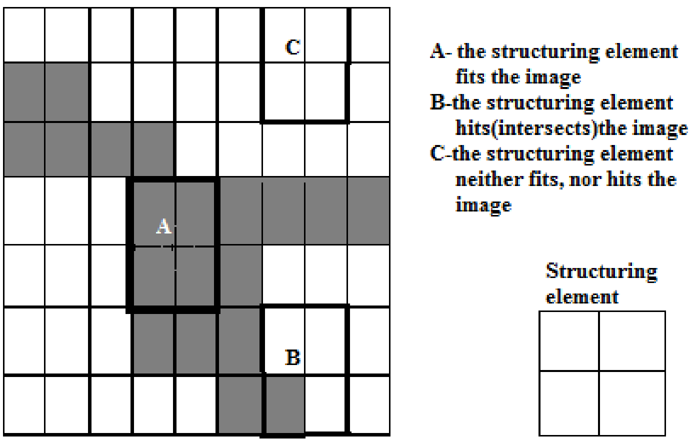

Fig.2 Probing of an image with a structuring element

The basic effect of the erosion operator on a binary image is to erode away the boundaries of regions of foreground pixels which are typically white pixels. As a result areas of foreground pixels shrink in size, and holes within those areas hence become larger. The erosion operator works as follows. It takes two pieces of data as inputs. The first piece is the image which is to be eroded and the second piece is a set of coordinate points known as a structuring element. It is this structuring element that will determine the precise effect of the erosion on the input image. The mathematical definition for erosion of binary image can be as follows: Suppose that X be the set of Euclidean coordinates corresponding to the input binary image, and K be the set of coordinates for the structuring element. Let K_x denotes the translation of K so that its origin will be at x. then the erosion of X by K is simply the set of all points x such that K_x is a subset of X.

To compute the erosion of a binary image by using structuring element, the foreground pixels in the input image is considered. For each foreground pixel which is also called as input pixel, superimpose the structuring element on top of the input image so that the origin of the structuring element coincides with the input pixel coordinates. If for every pixel present in the structuring element, the corresponding pixel in the underneath image is a foreground pixel, then the input pixel is left as it is i.e., it is not changed. If any of the corresponding pixels in the image are background, then the input pixel is also set to the background value.

The basic effect of the operator on a binary image is to gradually enlarge the boundaries of the regions of foreground pixels which are typically the white pixels. Thus the areas of foreground pixels grow in size while that of holes within those regions become smaller.

IV. Experimental Result

With the proposed method, change detection is extended to all types of images by using morphological processing. This method can clearly figure out every object present in the image. After obtaining difference maps of the image, a morphological operation called erosion is used for segmenting the difference maps into two classes: changed areas and unchanged areas. Fig. 3 represents the input image and Fig. 4 represents the segmentation results of the difference maps. It can be seen that with the proposed method the detection rate has increased compared to other methods.

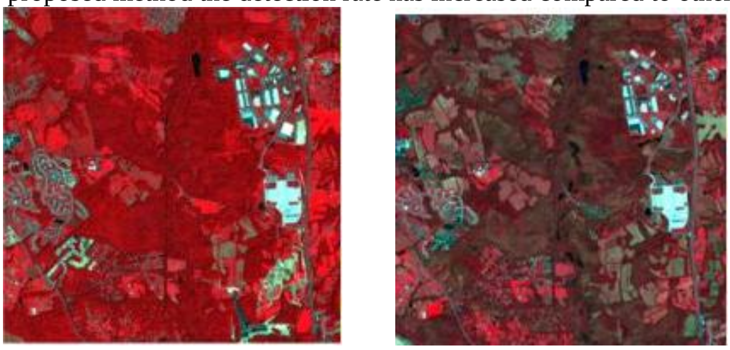

Fig. 3 Input image-Before change and After image

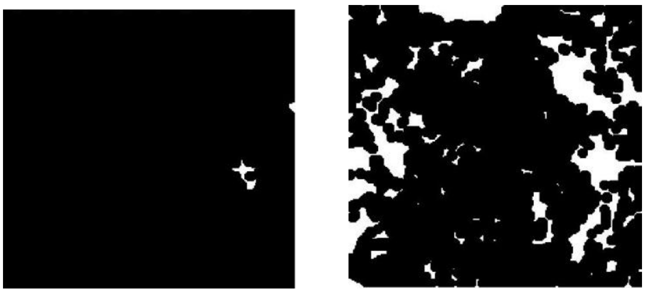

Fig. 4 Output image-Before change and After change

V. Conclusions

This paper has developed a new change detection method for all types of images. This has used SIRV distribution model for describing the coherency matrix of the image clutter. This model mainly estimates two parameters from the images for change detection: the texture τ and the covariance matrix of speckle ∑. The similarity measure calculation measures the similarity between the images. Morphological image processing will effectively perform the segmentation process. This will produce the difference map which efficiently point out the changes that have occurred in the image.This proposed method gives higher detection rate and lower false alarm rate. Also, by using morphological processing for segmentation, it helps to clearly figure out each object present in the image.

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