Survey on Change Detection in SAR Images

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ABSTRACT
Change detection in remote sensing images becomes more and more important for the last few decades, among them change detection in Synthetic Aperture Radar (SAR) images are having some more difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise. In this paper the Systematic survey of the common processing steps and core decision rules for change detection in SAR images has been carried out. Basically change detection in SAR images is divided in two steps a) Generating difference image & b) Detection of change in difference image, hence in this paper we also discuss various methods to generate difference image along with the change detection algorithm.

Keywords
Synthetic Aperture Radar (SAR), difference image, image fusion, image change Detection algorithms

1. INTRODUCTION
Change Detection is a process that analyzes pair of images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates [1]. Remote sensing [2], [3], medical diagnosis [4], [5] and video surveillance [6], [7] are the applications where Change detection techniques are used. Many common processing steps and core algorithms are used for change detection despite of its diversity of applications. This paper presents a survey of these Change detection methods and algorithms. Change detection is process of analyzing the two preprocessing SAR images acquired over the same geographical area at different times. Such an analysis is called unsupervised when it aims at discriminating between two opposite classes (which represent changed and unchanged areas) without any prior knowledge about the scene (i.e., no ground truth is available for modeling the classes).

Unsupervised Change Detection in SAR images can be divided in three steps: 1) image preprocessing; 2) Producing difference image between the multitemporal images; and 3) analysis of the difference image. In first step, to preprocess

The images the tasks mainly include coregistration, geometric corrections, and noise reduction. In the second step, two co registered images are compared pixel by pixel to generate the difference image. For the remote sensing images, differencing (subtraction operator) and rationing (ratio operator) are well known techniques for producing a difference image. In differencing, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal images. In rationing, changes are obtained by applying a pixelby- pixel ratio operator to the considered couple of temporal images. However, in the case of SAR images, the ratio operator is typically used instead of the subtraction operator since the image differencing technique is not adapted to the statistics of SAR images and non robust to calibration errors [8], [9]. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale [10], [11]. In the third step, to detect the changes a decision threshold to the histogram of the difference image is usually applied. To determine the threshold in an unsupervised manner several thresholding methods like Otsu, the Kittler and Illingworth minimum-error thresholding algorithm (K& I), and the Expectation Maximization (EM) algorithm [12] are proposed.

Fan Wang et al. [13] proposed a change-detection method based on the TMF model. The triplet Markov field (TMF) model is powerful in the non stationary synthetic aperture radar (SAR) image analysis. Taking the speckle noise and the correlation of non stationarities in two multitemporal SAR images into account.

Zheng et al. [14]proposed a new approach for change detection in multitemporal synthetic aperture radar images. Considering about the existence of speckle noise, the local statistics in a sliding window are compared instead of pixelby-pixel comparison.

Gong et al. [16] proposed an unsupervised distribution-free change detection approach for synthetic aperture radar (SAR) images based on an image fusion strategy and a novel fuzzy clustering algorithm. The image fusion technique is introduced to generate a difference image by using complementary information from a mean-ratio image and a log-ratio image.

Cihlar et al. [17], show the usefulness of multitemporal SAR images acquired over an annual cycle to monitor the changes occurring on the land surface. The change-detection task is carried out by a simple thresholding of the cumulative histogram of the difference image on the basis of predefined threshold values. In order to minimize the speckle effect, the authors applied a 5_5 mean filter to the difference image. Because of the multiplicative nature of speckle noise, it appears more effective to use the ratio operator than the difference operator to compare two SAR temporal images [9] [30].

R. J. Dekker [18] proposed a method based on the generation of a logarithmic-scaled ratio image from a couple of multitemporal SAR images, followed by an adaptive filtering and a simple thresholding procedure applied according to a manual selection of the decision threshold.

Grover et al. [19] proposed a method in which the original images are preprocessed in different ways (i.e., block averaging, Gamma MAP filter, image segmentation), and changes are identified by manually thresholding the log-ratio image generated from the filtered images according to a desired probability of false alarms. This paper is organized into four sections. In the next section, we discussed Image Preprocessing methods. Section 3 describes the change detection methods in detail. The last section presents our conclusions.

2. PREPROCESSING METHODS

The goal of a change detection algorithm is to detect significant changes while rejecting unimportant ones. Sophisticated methods for making this distinction require detailed modeling of all the expected types of changes (important and unimportant) for a given application and integration of these models into an effective algorithm. In next subsection various preprocessing steps are describe which are used in order to remove common type of unimportant changes before making the change detection decision.

2.1 Geometric Adjustments

In change detection algorithms the main preprocessing step is image co-registration, the alignment of several images into the same coordinate frame. Registration can be performed when area of interest are rigid in nature and the motion of camera is small, low dimensional spatial transformations such as similarity, affine, or projective transformations are often be used to perform registration. In several excellent survey like [31] and [32] this estimation problem has been well studied and software implementations (e.g., the Insight toolkit [33]) are available, so we do not detail registration algorithms here. Rather, we note some of the issues that are important from a change detection standpoint. Appropriate spatial transformation should be selected for good change detection, choosing a spatial transformation for any application is a critical task. For example a 12-parameter quadratic model is sufficient for registration of curved human retinal images [34], while affine transformation is proven to be inadequate. Now a days modern registration algorithms are available which are capable of switching automatically to higher order transformations after being initialized with a loworder similarity transformation [35]. Selection of feature-based, intensity-based, or hybrid registration algorithms is another practical issue regarding registration. In case of selection of feature-based algorithms, the accuracy of the registration algorithm totally depends on accuracy of the feature itself. The possibility of localized registration errors which can result in false change detection must be considered, even when average/global error measures appear to be modest.

2.2 Noise Reduction

Speckle is an important type of noise in Synthetic Aperture Radar images. There is sizable body of research on modeling and suppression of speckle (for example, see [36], [37] and the survey by Touzi [38]). Various methods like local spatial averaging (albeit at the expense of spatial resolution), thresholding, frame averaging (assuming speckle is uncorrelated between successive images)and statistical model-based and/or multiscale filtering are available to remove speckle noise from the image.

3. CHANGE DETECTION METHODS AND ALGORITHMS

In the past years a variety of change detection techniques have been developed. In this section, we focus on describing change detection algorithms.

3.1 Triplet Markov Field Model

Assuming that S is the set of image pixels, $I_0 = (I_{0s})s\epsilon S$ and $I_1 = (I_{1s})s\epsilon S$ denote the two multitemporal SAR images acquired over the same area at different times. In the unsupervised change detection in the SAR images, the absolutevalued logratio image is computed as the observable image $Y = (Y_s)s\epsilon S$, i.e.,

$$Y = |log\frac{I_0}{I_1}| \quad (1)$$

Represented as $X = (X_s)_{s\epsilon S}$, the change detection is a hidden Markov field and needs to be estimated from Y . Each X_s possesses a label in the set {0,1}, indicating no-change or change, respectively. It converts to a Bayesian statistical classification on Y, with maximum a posteriori (MAP) criterion or maximum posterior marginal (MPM) criterion. The MPM criterion, which maximizes $p(xs|y)$ for each $s\epsilon S$, is proved to be more appropriate than the MAP [15] due to its reasonable cost assignments to incorrect classified pixels. Thus, the MPM criterion is used with the TMF model to estimate the changes from Y.

3.2 Radon Transform and Jeffrey Divergence

Let us consider two coregistered SAR images I_X and I_Y cquired over the same geographical area at two different dates. The goal is to generate a "change/no change" map identifying the changes that occurred during the two dates. The problem can be decomposed into two steps: the generation of a change image and the thresholding of the change image. The process is applied for each possible pixel position (i, j) within the image area. The local neighborhoods of pixel (i, j) in the before and after images form two colocated analysis windows X and Y , respectively. Then, at each pair of analysis window, the following processing stages are performed.

3.2.1 Radon Transform Stage:

Apply the Radon transform [14] to the subimages in the sliding windows, respectively, to generate a pair of projections to be compared. In order to reduce the loss of information, we also gain the perpendicular projections.

3.2.2 Jeffrey Divergence Stage:

Apply the Jeffrey divergence [14] as the distance measure between the two pairs of projections. The probability density used in the Jeffrey divergence is approximated by Edgeworth expansion. The well-known "receiving operator characteristic" (ROC) curves are introduced to evaluate the quality of the change image, independently of the choice of the thresholding algorithm. It assesses how sensitive the detection probability P_{det} is to the false alarm probability P_{fa}.

3.3 Reformulated FLICM Algorithm

Krinidis et al. [29] proposed a new algorithm called Fuzzy local information C-means(FLICM). FLICM enhances the clustering performance.

3.3.1 FLICM Clustering Algorithm

The characteristic of FLICM is the use of a fuzzy local similarity measure, which is aimed at guaranteeing noise in-sensitiveness and image detail preservation. In particular, a novel fuzzy factor $G_{(ki)}$ is introduced into the object function of FLICM to enhance the clustering performance. This fuzzy factor can be defined mathematically as follows:

$$G_{ki} = \sum_{\substack{j\epsilon N_i \\ i\neq j}} \frac{1}{d_{ij}+1}(1-u_{kj})^m \parallel x_j - v_k \parallel^2 \quad (4)$$

where the i^{th} pixel is the center of the local window, the j^{th} pixel represents the neighboring pixels falling into the window around the i^{th} pixel, and d_{ij} is the spatial Euclidean distance between pixels i and j, v_k represents the prototype of the center of cluster k , u_{kj} and represents the fuzzy membership of the gray value j with respect to the k^{th} cluster. By using the definition of G_{ki} , the objective function of the FLICM can be defined in terms of

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c}[u_{ki}^m \parallel x_i - v_k \parallel^2 + G_{ki}] \qquad (5)$$

where v_k represents the prototype value of the k^{th} cluster and u_{ki} represents the fuzzy membership of the i^{th} pixel with respect to cluster k, N is the number of the data items, and c is the number of clusters. $||x_i\text{-}v_k||^2$ is the Euclidean distance between object and the cluster center v_k. In addition, the calculation of the membership partition matrix and the cluster centers is performed as follows:

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}}\right)^{\frac{1}{m-1}}}. \qquad (6)$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^m x_i}{\sum_{i=1}^{N} u_{ki}^m}. \qquad (7)$$

where the initial membership partition matrix is computed randomly. Finally, the FLICM algorithm is given as follows.

Step 1) Set the number c of the cluster prototypes, fuzzification parameter m and the stopping condition ε.

Step 2) Initialize randomly the fuzzy partition matrix.

Step 3) Set the loop counter b = 0.

Step 4) Compute cluster prototypes using (6).

Step 5) Calculate the fuzzy partition matrix using (5).

Step 6) If max $\{U^b\text{-}U^{b+1}\} < \varepsilon$ then stop, otherwise, set b=b+1 and go to step 4

3.3.2 Reformulated FLICM

Gong et al. [16] described a method based on Image Fusion and Fuzzy Clustering. They proposed an unsupervised distribution-free SAR-image change detection approach. They proposed improved FLICM. In [29] the fuzzy factor G_{ki} cannot able to suppress influence of noisy pixels effectively. Due to the above mentioned disadvantage fuzzy factor G_{ki} is modified. New improved fuzzy factor is given by

$$G'_{ki} = \begin{cases} \sum_{j\epsilon n_i} \frac{1}{2+min((C_u^j/C_u)^2,(C_u/C_u^j)^2)} \\ \times(1-u_{kj})^m \parallel x_j - v_k \parallel^2 \quad ifC_u \geq \overline{C_u} \\ \sum_{j\epsilon n_i} \frac{1}{2-min((C_u^j/C_u)^2,(C_u/C_u^j)^2)} \\ \times(1-u_{kj})^m \parallel x_j - v_k \parallel^2 \quad ifC_u < \overline{C_u} \end{cases} \qquad (8)$$

where C_u is the local coefficient of variation of the central pixel, C^j_u represents the local coefficient of variation of neighboring pixels, C_u and is the mean value of that is located in a local window. As shown in (16), the reformulated factor G'_{ki} balances the membership value of the central pixel taking into account the local coefficient of variation, as well as the gray level of the neighboring pixels. If there is a distinct difference between the results of the local coefficient of variation that are obtained by the neighboring pixel and the central pixel, the weightings added of the neighboring pixel in G'_{ki} will be increased to suppress the influence of outlier; thereby, the reformulated FLICM, i.e., termed as RFLICM, is expected to be more robust to its pre-existence.

Finally, by taking the place of in FLICM with the new fuzzy factor, the RFLICM algorithm can be summarized as follows.

Step 1) Set the values of c, m & ε.

Step 2) Initialize randomly the fuzzy partition matrix & the loop counter b=0.

Step 3) Calculate the cluster prototypes (6).

Step 4) Compute the partitioning matrix (5).

Step 5) If max $\{U^b\text{-}U^{b+1}\} < \varepsilon$ then stop, otherwise, set b=b+1 and go to step 3

4. CONCLUSION

The change detection algorithm most actively used in two application domains those are remote sensing and video surveillance, and their approach to the problem are often quite different. we have attempted to survey the recent state of change detection in SAR images. The TMF [13] method can achieve better detection result with a high detection rate and a low false-alarm rate simultaneously. A new similarity measure [14] between two distributions in the context of multitemporal SAR image change detection. This measure is based on the Radon transform combined with Jeffrey divergence. The change map is produced by comparing the pdfs of the projections that are generated by Radon transform. While Maoguo Gong et al. [15] uses wavelet based fusion method to generate the difference (fuse) image. The fuse image in this is generated by complementary information from both log ratio and mean ratio operator. For the Change detection RFLICM algorithm is used which incorporates both local spatial and gray information and it is relatively insensitive to probability statistics model. The RFLICM algorithm introduces the new factor G_{ki} as a local similarity measure to make a tradeoff between image detail and noise.

5. REFERENCES

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