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Change Detection in SAR Images using Image Fusion and RFLICM

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***Abstract* – The change detection techniques used previously were not much efficient. Therefore a new technique called an unsupervised distribution-free change detection approach is presented for synthetic aperture radar (SAR) images based on an image fusion strategy and a novel fuzzy clustering algorithm in this paper. In this technique the image fusion scheme is used to generate a difference image. The mean-ratio image and a log-ratio image are used as inputs for image fusion scheme. Wavelet fusion rules based on an average operator and minimum local area energy are chosen to fuse the wavelet coefficients for a low-frequency band and a high-frequency band respectively are used in image fusion. To classify changed and unchanged regions in the fused difference image a reformulated fuzzy local information C-means clustering algorithm is proposed. It enhances the changed information and of reduces the effect of speckle noise.**

***Keywords* – SAR, Speckle Noise, Image Fusion, Change Detection, Reformulated Fuzzy Local Information C-Means Clustering.**

I. Introduction

Synthetic aperture radar is a imaging radar which operates in any weather conditions and provides high resolution. So it has various applications like Reconnaissance, Surveillance, and Targeting, Foliage and Ground Penetration etc. Image change detection [2],[10] is a process that analyses images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates [1].Change detection in synthetic aperture radar (SAR) images exhibits some difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise which degrades the quality of image. However, SAR sensors are independent of atmospheric and sunlight conditions, which make the change detection in SAR images still attractive [1], [4], [11].

An unsupervised change detection [8] in SAR images can be divided into three steps: 1) image preprocessing; 2) producing difference image between the images; and 3) analysis of the difference image. The tasks of the first step mainly include co registration, geometric corrections, and noise reduction. In the second step, two 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 technique, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal images. And in rationing, changes are obtained by applying a pixel-by pixel ratio operator to the considered couple of temporal images. However, in the case of SAR images, instead of differencing the ratio operator is typically used operator because the image differencing technique is not adapted to the statistics of SAR images and non-robust to calibration errors [4]. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale [2].With the log ratio operator, the multiplicative speckle noise can be transformed in an additive noise component.

Furthermore, the range of variation of the ratio image will be compressed and thereby enhances the low intensity pixels while weakening the pixels in the areas of high intensity; therefore, the distribution of two classes (changed and unchanged) could be made more symmetrical. However, the information of changed regions that is obtained by the log-ratio image may not be able to reflect the real changed trends in the maximum extent because of the weakening in the areas of high-intensity pixels. As for the ratio mean operator, the background (unchanged regions) of mean-ratio image is quite rough, for the ratio technique may emphasize the differences in the low intensities of the temporal images. In the third step, changes are usually detected by applying a decision threshold to the histogram of the difference image. Several thresholding methods [3] have been proposed in order to determine the threshold in an unsupervised manner, such as Otsu, the Kittler and Illingworth minimum error thresholding algorithm (K&I), and the expectation maximization (EM) algorithm [9]. It is apparent that this kind of methods requires an accurate estimation of the decision threshold. Moreover, they need to select a proper probability statistical model for distribution of change and unchanged classes in the difference image, which leads to significant restrictions on their application prospect. Various fuzzy c-means clustering algorithms [5],[7],[8]were used in change detection like FCM_S, fast generalized FCM, FGFCM, and FLICM but all those were not much efficient. FCM was very sensitive to the speckle noise, in FCM_S the labelling of a pixel to be influenced by the labels in its immediate neighbourhood. However, compared with the

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original FCM, the computational complexity of FCM_S is significantly increased since it computes the neighbourhood term in each iteration step FGFCM significantly reduced the execution time by clustering on gray-level histogram rather than on pixels; meanwhile, It is less sensitive to noise to some extent because of the introduction of local spatial information. An artificial parameter is applied in their objective functions in order to balance between robustness to noise and effectiveness of preserving the details of the image. The selection of parameter is not easy to implement since there is no prior knowledge about the speckle noise level. FLICM introduced a term fuzzy factor which uses gray-level difference and spatial distance and use of spatial distance is not appropriate in some cases. Therefore a new algorithm is introduced.

In general, the whole performance of SAR-image change detection is mainly relied on the quality of the difference image and the accuracy of the classification method. In order to address the two issues, a new method which is an unsupervised distribution free SAR- image change detection approach is used. It is unique in the following two aspects: 1) producing difference images by fusing a mean-ratio image and a log-ratio image [6], and 2) improving the fuzzy local information c-means (FLICM) clustering algorithm [7], which is insensitive to noise, to identify the change areas in the difference image, without any distribution assumption.

II. Methodology

The two co registered intensity SAR images are consideredas

$X_1=\{x_1(i, j),1<i<H,1<j<W\}$ and

$X_2=\{x_2(i, j),1<i<H,1<j<W\}$,

i.e., acquired over the same geographical area at two different times and, respectively. Our objective is aiming at producing a difference image that represents the change information between the two times; then, a binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged. As shown in Fig. 1, the unsupervised distribution-free change detection approach is made up of two main phases: 1) generate the difference image using the wavelet fusion based on the mean-ratio image and the log-ratio image; and2) automatic analysis of the fused image by using an improved fuzzy clustering algorithm.

I. Generate the Difference Image Using Image Fusion

A discrete wavelet transform (DWT) is used for image fusion. The DWT isolates frequencies in both time and space, allowing detail information to be easily extracted from images. Fig. 2 shows implementation of a image fusion scheme using DWT. First the mean ratio operator and the log-ratio operator are applied to the two source images used for fusion respectively, which are commonly given by

$$X_m= 1-\min(\mu_1/\mu_2, \mu_2/\mu_1) \quad (1)$$

$$X_l= |\log(X_2/X_1)| \quad (2)$$

where μ_1 and μ_2 represent the local mean values of multi temporal SAR images X_1 and X_2, respectively.

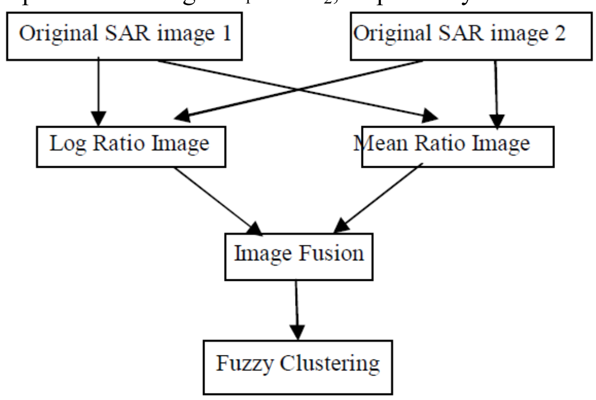

Fig.1. Flowchart of the proposed change detection approach [1].

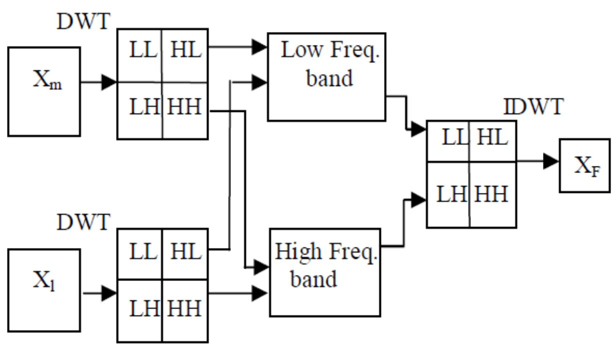

Fig.2. Image fusion technique based on DWT [1]

Figure 2 shows an image fusion technique based on DWT. In this image fusion scheme based on the wavelet transform, wavelet coefficient map is obtained by taking DWT of log ratio and mean ratio images. After that fusion rules are applied. Here, two main fusion rules are applied: the rule of selecting the average value of corresponding coefficients for the low-frequency band, and the rule of selecting the minimum local area energy coefficient for the high frequency band. The fusion rules can be described as follows:

$$D^F_{LL}=(D^m_{LL}+D^l_{LL})/2 \quad (3)$$

$$D^F_{\varepsilon}= \begin{cases} D^m_{\varepsilon}(i,j), & E^m_{\varepsilon}(i,j) < E^l_{\varepsilon}(i,j) \text{ or} \\ D^l_{\varepsilon}(i,j), & E^l_{\varepsilon}(i,j) >= E^m_{\varepsilon}(i,j) \end{cases} \quad (4)$$

where *m* and *l* represent the mean-ratio image and the log-ratio image, respectively. F denotes the new fused image. D_{LL} stands for low-frequency coefficients. $D^l_{\varepsilon}(i,j)$ represents three high-frequency coefficients at point (i, j)

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in the corresponding sub-images. The local area energy coefficient $E_{\varepsilon}(i,j)$ can be computed as follows:

$$E_{\varepsilon}(i,j)=\sum_{k\in N_{i,j}}\left|D_{\varepsilon}(k)\right| \quad (5)$$

where $E_{\varepsilon}(i,j)$ represents the local area energy of the wavelet coefficient at point (i, j) in the corresponding sub-image, and $N_{i,j}$ represents the local window centred on (i, j). $D_{\varepsilon}(k)$ denotes the value of the k^{th} wavelet coefficient that is around the local window. After that inverse DWT is taken to get the fused image.

II. Detect Changed Areas in the Fused Image Using the Improved FCM

In reformulated fuzzy local information c-means clustering algorithm the local coefficient of variation is adopted to replace the spatial distance in FLICM which is defined as:

$$C_u = \mathrm{var}(x)/(\bar{x})^2 \quad (6)$$

where var(x) and $\bar{x}$ are the intensity variance and the mean in a local window of the image, respectively. The value of Cu reflects the gray-value homogeneity degree of the local window.

The fuzzy factor for RFLICM can be defined as

$$G'_{ki}=\Sigma_{j\epsilon Ni}\,[\tfrac{1}{2}+\min((C^j_u/C_u)^2,(C_u/C^j_u)^2)]$$

$$[X(1-u_{kj})^m\|x_j-v_k\|^2 \quad \text{if } C^j_u >= \mathcal{T}_u$$

Or

$$G'_{ki}=\Sigma_{j\epsilon Ni}\,[\tfrac{1}{2}-\min((C^j_u/C_u)^2,(C_u/C^j_u)^2)]$$

$$[X(1-u_{kj})^m\|x_j-v_k\|^2 \quad \text{if } C^j_u < \mathcal{T}_u \quad (7)$$

where, v_k is prototype value of k_{th} cluster, u_{kj} is fuzzy membership of ith pixel with respect to cluster k, C^j_u is local coefficient of variation of neighbouring pixels, C_u is local coefficient of variation of central pixel and C_u is the mean value of C^j_u that is located in a local window.

The calculation of the membership partition matrix is performed as follows:

$$u_{ki}=1/\{\sum_{j=1}^{c}\{[(\|x_i-v_k\|^2+G'_{ki})/(\|x_i-v_j\|^2+G'_{ji})]^{1/(m-1)}\}\} \quad (8)$$

u_{ki} represents the fuzzy membership of the i^{th} pixel with respect to cluster k, and c is the number of clusters, $\|x_i-v_k\|^2$ is the Euclidean distance between object and the cluster centre.

Here, the reformulated factor balances the membership value of the central pixel taking into account the local coefficient of variation, as well as the gray level of the neighbouring pixels. If there is a distinct difference between the results of the local coefficient of variation that are obtained by the neighbouring pixel and the central pixel, the weightings added of the neighbouring pixel in will be increased to suppress the influence of outlier.

III. Results

Figure 3 shows original images taken by SAR. To generate difference image mean ratio and log ratio operators are applied to original images. Fig. 4. (a) and (b) shows results after applying the ratio operators and fig. 4. (c) shows result of image fusion scheme using wavelet transform.

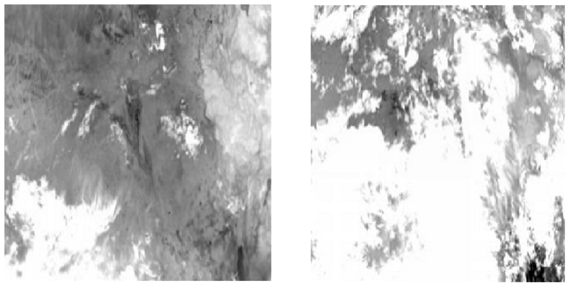
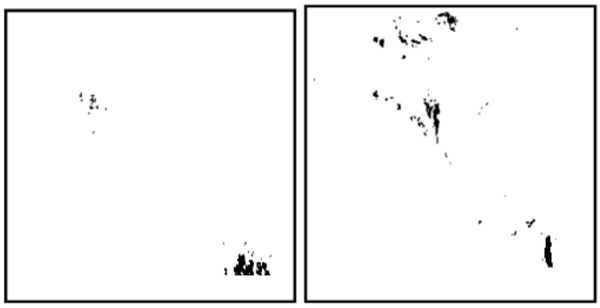
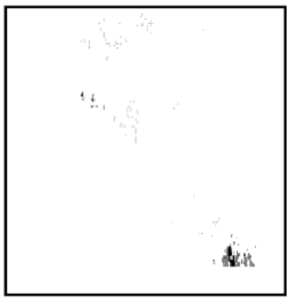


Fig.3. Original Images taken by SAR

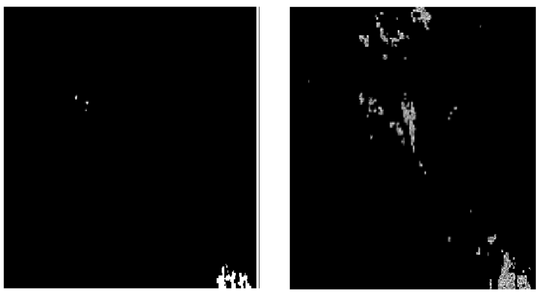


(a) (b)



(c)

Fig.4. Difference image using (a) Mean ratio operator (b) Log ratio operator and (c) Image fusion scheme.



(a) (b)

Fig.5. (a) FLICM image (b) RFLICM image.

Figure 5 (a) shows result obtained by FLICM clustering algorithm and (b) and shows result of RFLICM algorithms respectively.

IV. Conclusion

In this method, the information of changed regions reflected by the mean-ratio image is relative in accordance with the real changed trends in multi temporal SAR images. On the other hand, the information of background obtained by the log-ratio image is relatively flat on account of the logarithmic transformation. Hence, complementary information from the mean-ratio image and the log-ratio image is utilized to fuse a new difference image. So the difference image obtained by image fusion is more accurate. Here, the RFLICM algorithm that incorporates both local spatial and gray information is used, which is relatively insensitive to probability statistics model. The RFLICM algorithm introduces the reformulated factor as a local similarity measure to make a trade-off between image detail and noise. So, the proposed wavelet fusion strategy integrates the advantages of the log-ratio operator and the mean-ratio operator and gain a better performance. The change detection results obtained by the RFLICM exhibited more accuracy than its pre-existence (i.e., FLICM).

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