Robust Change detection in SAR images with RFLICM by using Wavelet Fusion

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ABSTRACT

This paper presents robust change detection in SAR (Synthetic aperture radar) images are based on image fusion and reformulated fuzzy clustering. The proposed approach is used both mean-ration and log-ratio for to generate image to generate the DI (difference image) by image fusion technique. The wavelet technique is used to enhance the information of changed region is extracted form background information by using difference image is based on wavelet fusion. The proposed reformulated fuzzy local c means clustering algorithm is used for differentiating both changed and unchanged regions in fused image and it is insensitive to the noise reduce the effect of speckle noise. From this method we get efficient results and lower error than compare to existing techniques.

Keywords: FCM, SAR, Image Fusion.

I. INTRODUCTION

Detecting regions of changes in geographical area at Different times is of widespread interest due to large Number of applications in diverse disciplines. It plays in important role in different domains like on land use/land cover dynamic, medical diagnosis, remote sensing, analysis of deforestation process, video surveillances. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Synthetic Aperture Radar (SAR) imagery has found important applications due to its clear advantages over optical satellite imagery one of them being able to operate in various weather condition However, there are problems associated with the nature of the radar imaging process due to the comparability of the wavelength to surface roughness. The presence of speckle noise degrades SAR images significantly and may hide important details on the images, leading to the loss of crucial information. Change detection in SAR images is based on a three-step procedure

1) Preprocessing
2) Producing difference image between the multi-temporal images and
3) Analysis of the difference image.

The aim of Preprocessing includes registration, geometric corrections, and noise reduction. In the second step, the two pre-processed images are taken as input and Compared pixel by pixel and thereafter another image is generated, called the difference image. Mainly there is subtraction operator (in which co registered images are compared pixel by pixel to generate difference image) and rationing (ratio operator) are well-known techniques for producing difference image. In SAR images, the ratio operator is well suited than subtraction operator. In the last step, a decision threshold is applying to the histogram of the difference image to detect the changes. There are several methods to determine the threshold the Kittler and Illingworth minimum- error thresholding Otsu, Bayesian minimum error decision rule and the expectation maximization (EM) algorithm. In general, we can clear from literature the performance of SAR image change detection is mainly depend on the quality and accuracy of the difference image and the classification method. Following two aspects are used in this paper. In order to address the two issues, in this paper, we propose an unsupervised distribution-free SAR image Change detection approach. It is unique in the following two aspects: 1) producing difference images by fusing a mean-ratio image and a log-ratio image, and 2) improving the fuzzy local-information c-means (FLICM) clustering algorithm, which is insensitive to noise, to identify the change areas in the difference image, without any distribution assumption. The fuzzy clustering methods that is, fuzzy c-means (FCM) algorithm which is the most method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information. By this method we can avoid the effect of speckle noise and to identify the changed areas in the difference image.

II. RELATED WORK

Let us consider the two co registered intensity SAR images, $X1 = \{X1(i, j), 1 < i < H, 1 < j < W\}$ and $X2 = \{X2(i, j), 1 < i < H, 1 < j < W\}$ of size H x W, acquired over the same area at different times t1 and t2. Our aim is to compute the difference image that represents the change information. Change detection approach is made up of two classes.

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1) Generate difference image using the wavelet function based on mean-ratio and log- ratio images and
2) Automatic analyzing of difference image using fuzzy clustering algorithm.

From the Fig.1 we can analyze this. The two images are co-registered taken at different date are time in order to find the changed area after co-registering applying log ratio and mean ratio operator from these two changed regions in both the regions are detected after this apply image fusion rule like DWT to get the fused image of changed regions different fused rules are applied for two low and high frequency bands after getting fused image clustering algorithm are applied to detect the changed and unchanged regions so the changed area is detected and analyzed The difference image enhances the background information as well as the changed information. Thus the image fusion introduced the effect of log-ratio and mean ratio operator and we can introduce the difference image. The difference image is expressed in mean scale and logarithmic due to the presence of speckle noise. The two images from the mean-ratio operation and log-ratio operation are fused to get the difference image. The main Disadvantage of the log-normal distribution fails to model the lower half of the SAR histograms. But it is able to reflect the changes in the maximum trend because of the weakening in low pixel values.

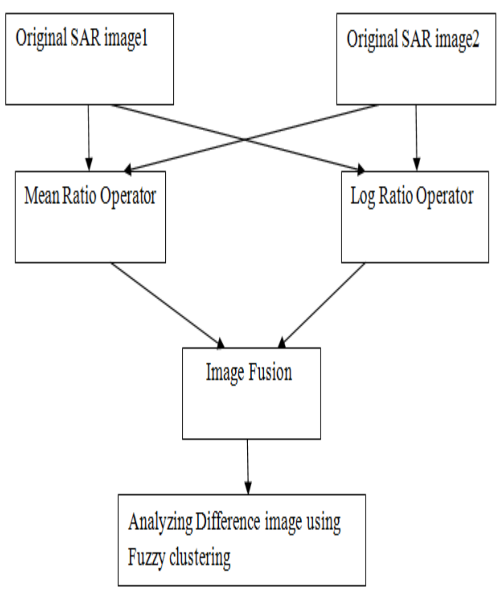

Fig.1. Flowchart of the proposed change detection approach

Image change detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates. In the last decades, it has attracted widespread interest due to a large number of applications in diverse disciplines such as remote sensing, medical diagnosis and video surveillance. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Among them, change detection in synthetic aperture radar (SAR) images exhibits some more difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise. However, SAR sensors are independent of atmospheric and sunlight conditions, which make the change detection in SAR images still attractive.

III. PROPOSED METHOD

Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed. Some examples of measures that can be used as in clustering include distance, connectivity, and intensity. In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

Fuzzy C means Clustering (FCM)

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal to one. After each iteration membership and cluster centers are updated according to the formula:

$$\mu_{ij}=1/\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(2/m-1)} \quad (1)$$

$$v_j = \left(\sum_{i=1}^{n}(\mu_{ij})^m xi\right)/\left(\sum_{i=1}^{n}(\mu_{ij})^m\right), \forall_j = 1,2 \ldots c \quad (2)$$

Where n is the number of data points, $'vj'$ represents the j^{th} cluster center $'m'$ is the fuzziness index m € [1, ∞]. $'c'$ represents the number of cluster center. $'\mu ij'$ represents the membership of i^{th} data to j^{th} cluster

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center. $'dij'$ represents the Euclidean distance between i^{th} data and j^{th} cluster center.

Main objective of fuzzy c-means algorithm is to minimize:

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^m \|x_i - v_j\|^2 \quad (3)$$

where, $'||x_i - v_j||'$ is the Euclidean distance between i^{th} data and j^{th} cluster center.

Algorithmic steps for Fuzzy c-means clustering

Let X = {x_1, x_2, x_3 ..., x_n} be the set of data points and V = {v_1, v_2, v_3 ..., v_c} be the set of centers.

1) Randomly select *'c'* cluster centers.

2) Calculate the fuzzy membership $'\mu_{ij}'$ using:

$$\mu_{ij} = 1/\sum_{k=1}^{c} (d_{ij}/d_{ik})^{(2/m-1)}$$

3) Compute the fuzzy centers $'v_j'$ using:

$$v_j = \left(\sum_{i=1}^{n} (\mu_{ij})^m xi\right) / \left(\sum_{i=1}^{n} (\mu_{ij})^m\right), \forall_j = 1,2 \dots c$$

4) Repeat step 2) and 3) until the minimum *'J'* value is achieved or $||U^{(k+1)} - U^{(k)}|| < \beta$.

where,

'k' is the iteration step.

'β' is the termination criterion between [0, 1].

'U = $(\mu_{ij})_{n*c}$' is the fuzzy membership matrix.

'J' is the objective function.

FLICM Clustering Algorithm:

The characteristic of FLICM is the use of a fuzzy local similarity measure, which is aimed at guaranteeing noise insensitiveness 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:

$$G_{ki} = \sum_{j \in N_i} 1/d_{ij} + (1 - u_{kj})^m \|x_j - v_k\|^2 \quad (4)$$

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 , and u_{kj} represents the fuzzy membership of the gray value j with respect to the k^{th} cluster. It can be seen that factor is G_{ki} formulated without setting any artificial parameter that controls the tradeoff between image noise and the image details. In addition, the influence of pixels within the local window in G_{ki} is exerted flexibly by using their spatial Euclidean distance from the central pixel. Therefore, can reflect the damping extent of the neighbors with the spatial distances from the central pixel. However, compared with the FLICM, the artificial parameter that is applied in FCM_S and FGFCM is relatively difficult to vary adaptively with diverse spatial locations or distances from the central pixel. In general, with the application of the fuzzy factor G_{ki}, the corresponding membership values of the no-noisy pixels, as well as of the noisy pixels that is falling into the local window, will converge to a similar value and thereby balance the membership values of the pixels that are located in the window. Thus, FLICM becomes more robust to outliers. In addition, the characteristics of FLICM include noise immunity, preserving image details without setting any artificial parameter, and being applied directly on the original image.

$$u_{ki} = 1/\sum_{j=1}^{c} (\|x_i - v_k\|^2 + G_{ki}/\|x_i - v_j\|^2 + G_{ji})^{1/(m-1)} \quad (5)$$

$$v_k = \sum_{i=1}^{N} u_{ki}{}^m x_i / \sum_{i=1}^{N} u_{ki}{}^m \quad (6)$$

Finally, the FLICM algorithm is given as follows.

Step 1) Set the number of the cluster prototypes, fuzzification Parameter m and the stopping condition ∈ .

Step 2) Initialize randomly the fuzzy partition matrix.

Step 3) Set the loop counter b=0.

Step 4) Compute the cluster prototypes using (3).

Step 5) Calculate the fuzzy partition matrix using (2).

Step 6) $\max(U^{(b)} - U^{(b-1)}) < \in$ then stop; otherwise, set b=b+1, and go to step 4.

This proposed approach mainly focuses on the initialization of cluster centers for K-means. The data partitioning tries to divide data space into small cells or clusters where inter cluster distances are large as possible and intra cluster distances are small as possible. Consider a cutting plane perpendicular to X-axis used to partition the data. Let C1 and C2 be the first cell and the second cell respectively and $\overline{c1}$and $\overline{c2}$ be the cell centroids of the first cell and the second cell, respectively. The total clustering error of the first cell is thus computed by:

$$\sum_{c_i \in c_1} d(c_i, \overline{c1}) \quad (7)$$

and the total clustering error of the second cell is thus computed by:

$$\sum_{c_i \in c_2} d(c_i, \overline{c2}) \quad (8)$$

Where c_i is the ith data in a cell. As a result, the sum of total clustering errors of both cells is minimal.

$$d(c_i, \overline{c1}) <= d(c_i, c_m) + d(\overline{c1}, c_m).|c1| \quad (9)$$

$$d(c_i, \overline{c2}) <= d(c_i, c_m) + d(\overline{c2}, c_m) \quad (10)$$

$$\sum_{c_i \in c_1} d(c_i, \overline{c1}) <= \sum_{c_i \in c_1} d(c_i, c_m) + d(\overline{c1}, c_m).|c1| \quad (11)$$

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$\sum_{c_i \in c_2} d(c_i, \overline{c2}) <= \sum_{c_i \in 2} d(c_i, c_m) + d(\overline{c2}, c_m).|c2|$ (12)

m is considered as the partitioning data point where |C1| and |C2| are the numbers of data points in cluster C1 and C2 respectively. The total clustering error of the first cell can be minimized by reducing the total discrepancies between all data in first cell to m, which is computed by:

$\sum_{c_i \in c_1} d(c_i, c_m)$ (13)

The same argument is also true for the second cell. The total clustering error of the second cell is minimized by reducing the total discrepancies between all data in second cell to m, which is computed by the following equation.

$\sum_{c_i \in c_1} d(c_i, c_m)$ (14)

Where $d(c_i, c_m)$ is the distance between m and each data in each cell. Therefore the problem to minimize the sum of total clustering errors of both cells can be transformed into the problem to minimize the sum of total clustering error of all data in the two cells to m.

Finally, the RFLICM algorithm is given as follows.

Step 1) Set the number of the cluster prototypes, fuzzification Parameter m and the stopping condition ∈.

Step 2) Initialize randomly the fuzzy partition matrix.

Step 3) Set the loop counter b=0.

Step 4) Compute the cluster prototypes using (equation 6 in module2).

Step 5) Calculate the fuzzy partition matrix using (equation 5 in module2).

Step 6) max $(U^{(b)} - U^{(b-1)})$<∈ then stop; otherwise, set b=b+1, and go to step 4.

IV. SIMULATION RESULTS

Fig.2. Log Ratio Operator

Fig.3.Ground Truth Image

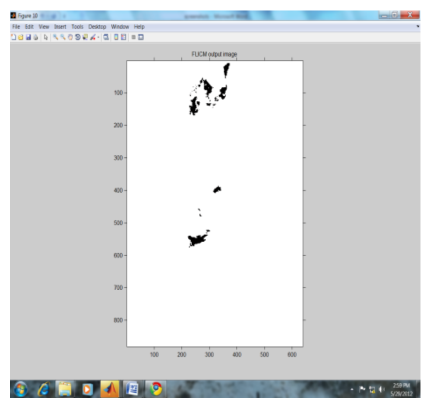

Fig.4. FLICM output

Fig.5. RFLICM output

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In this project first we perform mean ratio and log ratio on two original images and performing SWT based fusion image using new fusion rules and apply RFLCM and FLICM techniques on SWT based fusion image and finally compare the results of PCC and kappa values of both techniques.

V. CONCLUSION

In this project, we have presented a novel SAR-image change detection approach based on image fusion and an improved fuzzy clustering algorithm, which is quite different from the existing methods. First, for the wavelet fusion approach that we proposed, the key idea is to restrain the background (unchanged areas) information and to enhance the information of changed regions in the greatest extent. 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. Compared with other existing methods (mean ratio and log ratio), the proposed approach can reflect the real change trend as well as restrain the background (unchanged areas). Second, in contrast with the log-ratio image and the mean-ratio image, the estimation of the probability statistics model for the histogram of the fused difference image may be complicated since it incorporates both the log-ratio and mean-ratio image information at different resolution levels. Here, the RFLICM algorithm that incorporates both local spatial and gray information is proposed, which is relatively insensitive to probability statistics model. The RFLICM algorithm introduces the reformulated factor as a local similarity measure to make a tradeoff between image detail and noise. Compared with the original algorithms, RFLICM is able to incorporate the local information more exactly. The experiment results show that the proposed wavelet fusion strategy can integrate 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 less spots than its preexistence (i.e., FLICM) since it is able to incorporate the local information more exactly.

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