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Synthetic Aperture Radar Image Change Detection Using Fuzzy C-Means Clustering Algorithm

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Abstract: This paper presents a novel approach to change detection in synthetic aperture radar (SAR) images based on image fusion and fuzzy clustering. The proposed approach use mean-ratio image and log-ratio image to generate a difference image by image fusion technique. In order to enhance the information of changed regions and background information in the difference image is based on the wavelet fusion rule. A reformulated fuzzy local c means clustering algorithm is used for differentiating changed and unchanged regions in the fused image, which is insensitive to noise and reduce the effect of speckle noise. By this method we get a better performance and lower error than the pre-existence.

Keywords: Image fusion, clustering, fuzzy c-means algorithm (FCM), Synthetic Aperture Radar (SAR), image change detection.

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 [10], medical diagnosis [3], remote sensing [1], analysis of deforestation process, video surveillances [4]. 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 conditions.

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 [5]. In the literature, usually unsupervised change detection in SAR images is based on a three-step procedure 1) preprocessing;2) producing difference image between the multitemporal images; and 3) analysis of the difference image. The aim of preprocessing includes coregistration, 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 two coregistered 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 algorithm (K&I), Otsu, Bayesian minimum error decision rule and the expectation maximization (EM) algorithm [5]. Recently a few context-sensitive techniques using neural networks are also suggested.

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 [6], 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.

The rest of the paper can be organized as follows in section II, we discuss the main steps of the proposed approach and motivation. Section III mainly focuses on the description of proposed method in details, and in section IV, presents the experimental results on the real multi-temporal SAR images will be described in detail to

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demonstrate the effectiveness of the proposed approach. Finally the last section VI, presents our conclusion.

II. MOTIVATION

Let us consider the two coregistered 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. 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.

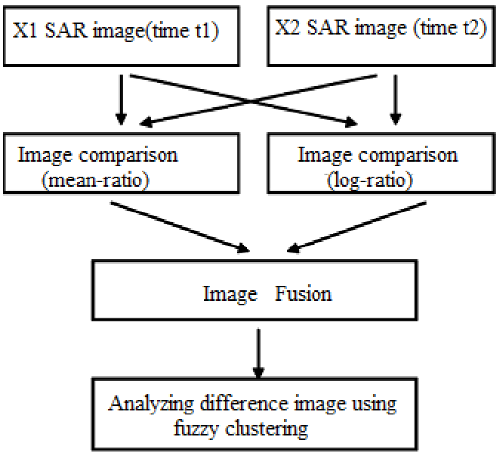

Fig. 1. Flowchart of the change detection approach.

A. *Generating Difference Images Using Image Fusion*

In section I, the difference image is expressed in mean scale and logarithmic due to the presence of speckle noise. By using the logarithmic we can convert the speckle noise into additive noise component. The mean ratio is also robust to speckle noise for this a ratio mean detector is used. Both methods are effective to detect the changes in image. 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 [7]. But it is able to reflect the changes in the maximum trend because of the weakening in low pixel values. In general, the optimal difference image have changed and unchanged areas. In which the changed area have larger pixel values and unchanged area have smaller pixel values [2].

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. From the above analysis we can conclude that the difference image that is fused by the mean-ratio and log-ratio image have better change information than the individual difference information.

B. Analyzing Difference Image Using Fuzzy Clustering

In this discriminate the changed areas from the unchanged regions of the difference image. The popular method as described in Section I to identify the changed regions are K&I algorithm, Otsu algorithm, and EM algorithm. And we use thresholding method for this and require accurate estimation of the thresholding value. Here a novel fuzzy c-means (FCM) clustering algorithm is used and it is insensitive to the probability statistics model of histogram is proposed to analyze the difference image. It has also to reduce the effect of speckle noise. The detail description of this method (novel fuzzy clustering) is described in Section III-B.

III. METHODOLOGY

In Section III, describes the proposed change detection approach, it consist two main steps:1) generate difference image based on image fusion 2) detect the changed areas in the fused image using fuzzy clustering.

A. Generate the Difference Image Using Image Fusion

In image fusion, the information is obtained in greater quality by using complementary information from different source images so that the new fused images is suitable for the purpose of the computed processing tasks. The image fusion techniques mainly take place at the pixel level of the source images [8]. In particular the transforms, such as the stationary wavelet transform (SWT), contourlets, etc., have been used for the pixel-level image fusion. The SWT isolates frequencies in both time and space, allow to extract the detail information from images. Compared with the other techniques SWT transforms are proved to have a better shift-invariance property and directional selectivity. The SWT concentrates on representing point discontinuities and preserving the time and frequency details in the image. Its simplicity and its ability to preserve image details with point discontinuities make the fusion scheme based on the SWT be suitable for the change detection task. The image fusion based on the wavelet transform can be described as follows: First, the SWT of each of the two source images are computed and second to obtain the decomposition of each source image. The two source images used for fusion are obtained from the mean-ratio operator and log-ratio operator as mentioned in Section II, and which are commonly given by

$$X_m = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right) \quad (1)$$

$$X_l = \left|\log \frac{X_2}{X_1}\right| = |\log X_2 - \log X_1| \quad (2)$$

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Where µ1 and µ2 are local mean values of SAR images X1 and X2.
The image fusion based on the wavelet transform can be described as follows: First, compute the SWT of each of the SAR images and obtain the multiresolution decomposition of each image. Then fuse the corresponding coefficients. In particular, the wavelet coefficients are fused together by using several fusion rules for a low-frequency band and a high-frequency band, respectively. Finally, the inverse SWT is applied to the fused multiresolution representation to obtain the fused image. Fig. 2 shows the process of the proposed image fusion based on the SWT.

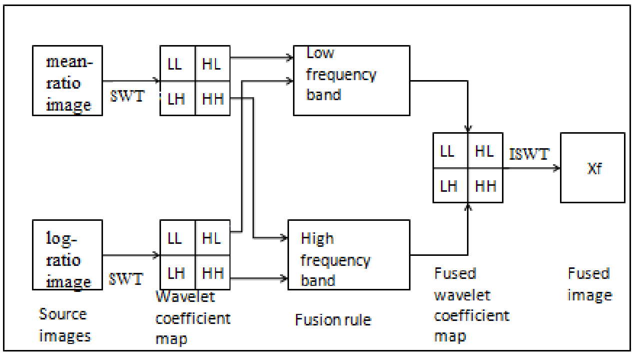

Fig. 2. Process of image fusion based on the SWT

Here the mean-ratio image (X*m*) and the log-ratio image (X*l*), respectively. H and L represent the high-pass and low-pass filters, in addition to these LL represents the approximate portion of the image, and LH, HL, and HH represents the horizontal, vertical, and diagonal direction portions. X*f* denotes the fused image.

In Fig.2, the two input images are decomposed into four sub-images of same size. In which the high frequency sub-bands are X^{LH1}, X^{HL1}, X^{HH1} which correspond to the horizontal, vertical, and diagonal direction portions, and get the information about the salient features of the source image such as edges and lines. The low-frequency sub-band X^{LL1} which gives the profile features of the input image.

The decomposition level can be obtained from low-frequency bands and high-frequency bands. It is necessary to fuse the wavelet coefficients using different fusion rules for the bands. The main issue of the proposed method to generate difference image is the selection of fusion rules, which should restrain the information of unchanged area and to enhance the information of changed regions. In the last few years, several types of fusion rules have been proposed, such as the rule of selecting the maximum absolute value of corresponding wavelet coefficients and the rule of selecting the coefficients from local features such as maximum variance or contrast. These rules are used to modify the magnitude of the coefficient of the fused image toward the maximum of that of the source images so that the gradient or edge features of the fused image are maximized. The main purpose of the fusion rule is to enhance the changed areas. But the background information in the difference image may become rough by maximizing the gradient or edge features of the fused image. Thus, it is necessary to develop an adaptive scheme for the fusion of input images which could restrain the background information and to enhance the information of changed regions in a larger way.

The two main fusion rules are: 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:

$$D^F_{\mathrm{LL}} = \frac{D^m_{\mathrm{LL}} + D^l_{\mathrm{LL}}}{2} \tag{3}$$

$$D^F_\varepsilon(i,j) = \begin{cases} D^m_\varepsilon(i,j), & E^m_\varepsilon(i,j) < E^l_\varepsilon(i,j) \\ D^l_\varepsilon(i,j), & E^m_\varepsilon(i,j) \geq E^l_\varepsilon(i,j) \end{cases} \tag{4}$$

Here m and l represents the mean-ratio image and log-ratio image and F denotes the new fused image. $D_\varepsilon(i,j)$ (ε =HH, LH, HL) are the three high frequency bands. The energy of the coefficients can be calculated as:

$$E_\varepsilon(i,j) = \sum_{k \in N_{i,j}} [D_\varepsilon(k)]^2 \tag{5}$$

here $E_\varepsilon(i,j)$ represents the energy of the wavelet coefficients at point (i,j) and $N_{i,j}$ represents the local window centered on(i,j). In above equation the wavelet coefficients of low frequency and high frequency are fused separately. The low-frequency sub-band gives the profile features of the input images and significantly reflects the information of changed regions of two images. Hence, in order to enhance the gradient or edge features of the changed regions, the rule of the average operator is selected to fuse the wavelet coefficients for the low-frequency sub-band. In the other hand, the high frequency sub-bands which indicate the information about the salient features of the source image such as edges and lines. And it also suppresses the speckle noise. This rule is used to merging the homogeneous regions of the high-frequency portion from the mean-ratio image and the log-ratio image. Considered the background of the log-ratio image is flat, the adoption of high frequency from the log-ratio image will help to inhibit the background in the new fused difference image. The proposed approach to generate the difference image is carried out in the multiresolution decomposition.

Comparing with the log-ratio image, the estimation of probability statistics model for the histogram of the fused

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difference image is very difficult. From the literature, the thresholding technique, such as K&I and EM, may be unable to analyze the fused difference image for the reason that both of them assume the histogram of the difference image correspond to the certain probability statistics model. Thus we can analyze the classification method that is insensitive to the probability statistics model of histogram is needful to analyze the fused difference image. In the next section, we proposed a novel FCM clustering algorithm for analyzing the difference image generated by the wavelet fusion.

B. Using FCM, Detect Changed Areas in the Fused Image

In fuzzy clustering methods, fuzzy c-means (FCM) algorithm [6] which is the popular method used in image segmentation due to its robust characteristics for ambiguity and can retain much more information than any other segmentation methods. Also the conventional Fuzzy C-Means algorithm works well on most noise-free images.

To improve the performance of image segmentation use FCM algorithm. In recent years many techniques are introduced, such as Tolias and Panas [2] developed a fuzzy rule-based scheme known as ruled-based neighborhood enhancement system which is to impose spatial constraints by post processing the FCM. Noordam proposed a geometrically guided FCM (GG-FCM) algorithm it is a semi-supervised FCM technique.

Ahmed *et al.* [9] proposed FCM_S where the objective function of the classical FCM is modified in order to compensate the intensity in homogeneity and allow the labeling of a pixel to be influenced by the labels in its immediate neighborhood. Cai *et al.*[9] proposed the fast generalized FCM (FGFCM) algorithm, which is used to reduce the execution time by clustering on gray-level histogram rather than on pixels. It is less sensitive to noise due to the introduction of local spatial information. After that Krindis and Chatzis [6] have proposed a robust FLICM clustering algorithm to remedy to all drawbacks. And we analysis of this algorithm and present our improvement.

1)Clustering Algorithm FLICM: several methods like FCM_S1, FCM_S2,EnFCM, and FGFCM and its variations, we propose, in this a novel and robust FCM for image clustering known as Fuzzy Local Information C-means (FLICM) clustering algorithm. In which new factor in FCM objective function is described. The new factor has some properties:

• To incorporate local spatial and local gray level information
in a fuzzy way in order to preserve robustness and noise insensitiveness;
• To control the neighborhood pixels depending on their distance from the central pixel;
• To be free to select any parameter.

The main function of the FLICM to enhance the clustering performance. The fuzzy factor can be described as:

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d_{ij}+1}(1-u_{kj})^m \|x_j - v_k\|^2 \qquad (6)$$

where the *ith* pixel is the center of the local window, is the reference cluster and the *j*th pixel belongs in the set of the neighbors falling into a window around the *i*th pixel d_{ij} is the spatial Euclidean distance between pixels *i* and *j*, u_{kj} is the degree of membership of the *i*th pixel in the *j*th cluster. The factor G_{ki} is formulated without setting any artificial parameter. The objective function of the FLICM is described in terms of

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c}\left[u_{ki}^m \|x_i - v_k\|^2 + G_{ki}\right] \qquad (7)$$

where v_k is the prototype value of the *k*th cluster and u_{ki} is the fuzzy membership of the *i*th pixel with respect to cluster k ,N represents the number of the data items, and c is the number of clusters. $\|x_i\text{-}vk\|^2$ is the Euclidean distance between the cluster center and object.

For computing the cluster prototype and fuzzy partition matrix using this formula:

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}}\right)^{1/(m-1)}} \qquad (8)$$

$$\nu_k = \frac{\sum_{i=1}^{N} u_{ki}^m x_i}{\sum_{i=1}^{N} u_{ki}^m} \qquad (9)$$

Finally the FLICM is described as:
Step 1) Set the number 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 the cluster prototypes .
Step 5) Calculate the fuzzy partition matrix.
Step 6) max $\{U^{(b)} - U^{(b+\,)}\} < \varepsilon$ then stop; otherwise, set $b=b+1$, and go to step 4.

2) Modification on FLICM: By analyzing the fuzzy factor G_{ki} the gray level information and the spatial information are represented by the gray level difference and spatial distances. The spatial change depends upon the

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spatial distances from the central pixel. When the neighborhood pixel with same gray level value has larger damping extent and vice versa. Also it exploits more local context information due to the local coefficients of variation of each pixel is computed in local window. Hence we modify the fuzzy factor G'$_{ki}$ and given as:

$$G'_{ki} = \begin{cases} \sum\limits_{j \in N_i} \frac{1}{2+\min\left((C_u^j/C_u)^2,(C_u/C_u^j)^2\right)} \\ \quad \times(1-u_{kj})^m \|x_j - v_k\|^2, & \text{if } C_u^j \geq \overline{C_u} \\ \sum\limits_{j \in N_i} \frac{1}{2-\min\left((C_u^j/C_u)^2,(C_u/C_u^j)^2\right)} \\ \quad \times(1-u_{kj})^m \|x_j - v_k\|^2, & \text{if } C_u^j < \overline{C_u} \end{cases}$$

By taking the new fuzzy factor in FLICM it is change to reformulated FLICM algorithm and described as:

Step 1) Set values for c, m, and ε .

Step2) Initialize randomly the fuzzy partition matrix and set the loop counter b=0.

Step 3) Calculate the cluster prototypes.

Step 4) Compute the partition matrix.

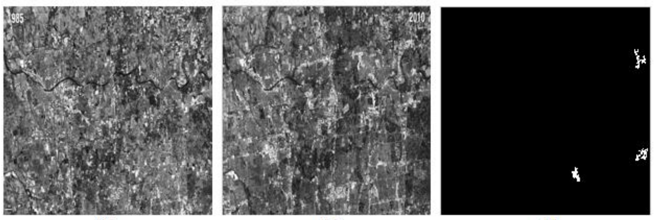
Step5) max $\{U^{(b)} - U^{(b+\ )}\} < \varepsilon$ then stop; otherwise, set b=b+1, and go to step 3).

III. EXPERIMENTAL STUDY

In this section, in order to validate the effectiveness of the proposed SAR-image change detection method, we will show the performance of the proposed methods by presenting numerical results on two data sets.

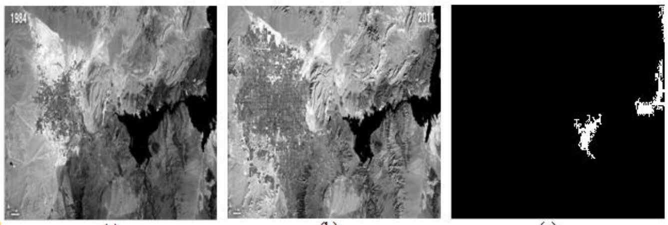
The first data set represents a section of two SAR images of chicaoland obtained in the years of 1985 and 2010 respectively shown in Fig.1(a) and (b). The influence of speckle noise on the image acquired in1985 is much greater than the image acquired in 2010. The available ground truth which was shown in Fig. 1(c), was created by integrating prior information with photo interpretation based on the input images Fig. 1(a) and (b).

The second data set is a section of two SAR images over the area of lasvegas.Fig. 2. Multitemporal images relating to lasvegas used in the experiments. (a)Image acquired in 1984 during the summer season. (b) Image acquired in 2011after the summer. (c) Ground truth. The available ground truth (reference image), i.e., shown in Fig. 2(c), was created by integrating prior information with photograph interpretation based on the input images Fig. 2(a) and (b).



(a) (b) (c)

Fig.1.Multitemporal images relating to the Chicagoland.(a) Image acquired in 1985. (b) Image acquired in 2010. (c) Ground truth.



(1 (a) (b) (c)

Fig.1.Multitemporal images relating to the Lasvegas. (a) Image acquired in 1984. (b) Image acquired in 2011. (c) Ground truth.

Two experiments have been carried out. The first experiment is aimed at the analyze the effectiveness of the wavelet fusion strategy to generate the difference image. And, we compared the change detection performance of our algorithm with other two methods, including the mean-ratio operator and the log-ratio operator. Then we analyzed the impact of the RFLICM algorithm onto the change detection results of the fused difference image. After this, we calculate the percentage correct classification (PCC). For this we need four quantities. They are,

- C_NC_D: Number of change pixels correctly detected.
- $C_{NN}C_D$: Number of no-change pixels correctly detected.
- C_NC_I: Number of change pixels incorrectly detected as no- change.
- $C_{NN}C_I$: Number of no-change pixels incorrectly detected as change.

These four quantities were used to calculate the percentage correct classification:

$$\text{PCC} = \frac{(C_NC_D + C_{NN}C_D)}{(C_NC_D + C_{NN}C_I + C_{NN}C_D + C_NC_I)} \qquad (11)$$

In this experiments, we analyzed the effectiveness of wavelet image fusion technique to generate the difference image. The difference images of the two region is shown in Fig.3. As shown in Table I, the change detection results of the fused difference image were compared with the ones generate from mean-ratio operator and log-ratio operator of the Chicagoland.

TABLE I
CHANGE DETECTON RESULT OF THE CHICAGOLAND

Difference image	CNNCI	CNNCI	PCC
Mean-ratio	14782	8	83.68%
Log-ratio	361	326	99.24%
Wavelet fusion	514	78	99.35%

And the proposed method resulted in the highest PCC value than any other technique.

IV. CONCLUSION

Wavelets are mathematical functions that decompose data or image into different frequency bands or components, and then study each component with a resolution matched to its scale. Wavelets have advantages over traditional Fourier transform, wavelet applicable in where the signal contains discontinuities and sharp spikes. In past wavelets are used for in the fields of mathematics, quantum physics and electrical engineering. But now the wavelet transform have new application the field of digital image processing, turbulence, human vision, radar, and earthquake prediction.

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 are better than the preexistence since it is able to incorporate the local information more exactly.

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