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Change Detection In Synthetic Aperture Radar Images Based On Fusion And Clustering Strategies

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***Abstract*—Generally, Change detection is the art of quantifying the changes in Synthetic Aperture Radar (SAR) images occurring over a period of time. This paper presents 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. In order to restrain the background information and enhance the information of changed regions in the fused difference image, 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. A reformulated fuzzy local information c- means clustering algorithm is proposed for classifying changed and unchanged regions in the fused difference image. It incorporates the information about spatial context in a novel fuzzy way for the purpose of enhancing the changed information and of reducing the effect of speckle noise. Experiments on real SAR images show that the image fusion strategy integrates the advantages of the log-ratio operator and the mean-ratio operator and gains a better performance. And finally the other feature to get the connectivity based clustering for change detection; the hierarchical clustering algorithm is used.**

***Index Terms*—Clustering, fuzzy C-means (FCM) algorithm, image change detection, image fusion, synthetic aperture radar (SAR), Fuzzy Local Information C-means (FLICM)**

I. INTRODUCTION

Change detection is an image enhancement technique that compares two images of the same area from different time periods. Identical picture elements are eliminated, leaving signatures that have undergone change. Detection of land-cover changes is one of the most interesting aspects of the analysis of temporal remote sensing images. In particular, it is very useful in many applications, like land use change analysis, study on shifting cultivation, monitoring of pollution, urban growth, assessment of burned areas, assessment of deforestation or other structural damage due to disaster, and so on. Unsupervised change detection in SAR images can be divided into three steps: 1) Image preprocessing, 2) Producing difference image between the multi temporal images and 3) Analysis of the difference image. Unsupervised change detection on SAR images are made more difficult, mainly for the following reasons:

- Image modality with the presence of speckle inherent to coherent imaging systems/sensors
- Difference of incidence angle (angle of sight and ascending/descending orbits) of the a acquisitions;
- Problems related to the difference of generation of radar sensors, which can occur when the two images are separated from several years (spatial resolution, inter calibration, ground segment, final product, etc.).

DWT concept based transformation of high resolution image using wavelet to four portions that three of them have high frequency and the one has low frequency. An inverse wavelet transformation is done for the three newly replaced images. These three images combined to one fused image. The fused image keeps in the high spatial resolution with the spectral information of the original multi-spectral image. It is unique in the following two aspects:

1) Producing difference images by fusing a mean-ratio image and a log-ratio image,
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 then

A. Related Works

In 2004, Turgaycelik et al.proposed Multiscale change detection in multi temporal synthetic aperture radar images which presented a an unsupervised change detection technique is developed by conducting probabilistic Bayesian inference with EM based parameter estimation.

The resulted final change detection mask at each scale could yield higher false detection due to image noise. In 2005, AllanAasbjerg Nielsen et al.suggested change detection in multi-and hyper spectral remote sensing data Change detection methods for multi-and hyper variant data aim at identifying differences in data acquired over the same area at different points in time.

Its main drawbacks are that:

1) It does not take full advantage of all the information present in the speckle the iterative filtering also reduces the Amount of information present in the speckle.
2) It is more focused on the thresholding task rather than on the correct estimation of changed and unchanged class statistics whose implicit estimations prove to be biased. In 2011 Madhurima Chattopadhyay et.al addressed the problem of change detection algorithm for medical cell images. In this the proposed method is tested on different images. It produced stable and fairly good results.

The main drawback is if the scenes under consideration have sufficient amount of varied illumination then this algorithm fails to detect the changed regions properly. In 2004, M.S.Yang et.al addressed the survey of fuzzy clustering. Here survey of fuzzy set theory applied in cluster analysis. These fuzzy clustering algorithms have been widely studied and applied in a variety of substantive areas.

They also become the major techniques in cluster analysis. In this paper, we give a survey of fuzzy clustering in three categories.

- The first category is the fuzzy clustering based on fuzzy relation.
- The second one is the fuzzy clustering based on objective function.

II. MOTIVATION

A. Motivation Of Generating Different Images Using Image fusion

As mentioned in above, the ratio difference image is usually expressed in a logarithmic or a mean scale because of the presence of speckle noise. In the past dozen years, there was a widespread concern over the logarithm of the ratio image since the log-normal model was considered as a heuristic parametric probability distribution function for SAR intensity and amplitude distributions. 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, and in, authors proposed a ratio mean detector (RMD), which is also robust to speckle noise. This detector assumes that a change in the scene will appear as a modification of the local mean value of the image.

B. Motivation Of Analyzing Different Image Using Fuzzy Clustering

The purpose to process the difference image is to discriminate changed regions from unchanged regions. As mentioned in Section I, the popular method to identify the changed regions, such as the K&I algorithm and the FM Algorithm, is usually carried out by applying a thresholding procedure to the histogram of the difference image. 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. In this paper, a novel fuzzy c-means (FCM) clustering algorithm that is insensitive to the probability statistics model of histogram is proposed to analyze the difference image. Specifically, this method incorporates the information about spatial context to the corresponding objective function for the purpose of reducing the effect of speckle noise.

III. PROPOSED METHOD

A. Input Images

SAR data has been less exploited than the optical one in the context of change detection. This is also due to the fact that SAR images suffer from the presence of the speckle noise that makes it difficult to analyze such imagery, and in particular to perform unsupervised discrimination between changed and unchanged classes. Despite the presence of speckle noise, the use of SAR sensors in change detection is potentially attractive from the operational viewpoint. 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. In fact, the ratio method is quite sensitive to the presence of image speckle in the sense that speckle patterns that are difficult to detect by a human eye in SAR images when the number of looks is large, will still be visible in ratio images.

Another important reason for selecting the ratio method instead of the difference method is that the ratio method is very robust to calibration errors whereas the difference method is not. First give the input two co-registered intensity SAR images acquired over the same geographical area at two different times t1and t2, respectively Producing a difference image that represents the change information between the two times. A binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged.

B. Generate the Difference Image

Ratio difference image is usually expressed in a logarithmic or a mean scale because of the presence of speckle noise. 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, and in, authors proposed a ratio mean detector (RMD), which is also robust to speckle noise.

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 RMD, the background (unchanged regions) of mean-ratio image is quite rough, for the ratio technique the optimal difference image should restrain the background (unchanged areas) information and should enhance the information of changed regions in the greatest extent. In order to address this problem, an image fusion technique is introduced to generate the difference image by using complementary information from the mean-ratio image and the log-ratio image in this paper.

The information of background obtained by the log-ratio image is relatively flat on account of the logarithmic transformation. The two source images used for fusion are obtained from the mean-ratio operator and the log-ratio operator, respectively, which are commonly given by

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

$$X_l = \left| \log \frac{X_2}{X_1} \right| = \left| \log X_2 - \log X_1 \log X1\right.$$

It's possible to generate the difference image in two ways such as

1) Generate the difference image based on image fusion, and

2) Detect changed areas in the fused image using the improved FCM.

1) Generate The Difference Image Using Image Fusion

Image fusion refers to the techniques that obtain information of greater quality by using complementary information from several source images so that the new fused images are more suitable for the purpose of the computed processing tasks. In the past two decades, image fusion techniques mainly take place at the pixel level of the source images. In particular, multi scale transforms, such as the discrete wavelet transform (DWT), curve lets, contour lets, etc., have been used extensively for the pixel-level image fusion.

2) Image Fusion Processing Using DWT

Image fusion refers to the techniques that obtain information of greater quality by using complementary information from several source images so that the new fused images are more suitable for the purpose of the computed processing tasks. In the past two decades, image fusion techniques mainly take place at the pixel level of the source images. In particular, multi scale transforms, such as the discrete wavelet transform (DWT), curve lets, contour lets, etc., have been used extensively for the pixel-level image fusion. The DWT isolates frequencies in both time and space, allowing detail information to be easily extracted from images.

Compared with the DWT, transforms such as curve lets and contour lets are proved to have selectivity. However, their computational complexities are obviously higher than the DWT. The DWT 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 DWT be suitable for the change detection task, particularly when massive volumes of source image data are to be processed rapidly.

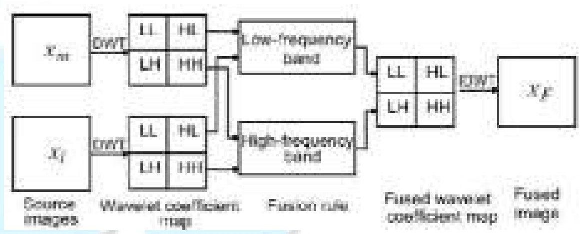

Fig 1: Process of Image Fusion Based On DWT

The image fusion scheme based on the wavelet transform can be described as follows: First, we compute the DWT of each of the two source images and obtain the multi resolution decomposition of each source image. Then, we fuse corresponding coefficients of the approximate and detail sub bands of the decomposed source images using the developed fusion rule in the wavelet-transform domain. In particular, the wavelet coefficients are fused using different fusion rules for a low-frequency band and a high-frequency band, respectively. Finally, the inverse DWT is applied to the fused multi resolution representation to obtain the fused result image. Fig. 1 shows the process of the proposed image fusion based on the DWT. Here X_m and X_l represent the mean-ratio image and the log-ratio image, respectively. H and L represent the high-pass and low-pass filters, respectively. In addition, LL represents the approximate portion of the image, and LH, HL, and HH denotes the horizontal, vertical, and diagonal direction portions, respectively. XF denotes the fused image. As shown in Fig. 1, each source image is decomposed into four images of the same size after one level of decomposition. The low frequency sub band XLL1, which is called the approximation portion, represents the profile features of the source image. Three high-frequency subbandsXLH1, XHL1 and XHH1 which correspond to the horizontal, vertical, and diagonal direction portions, show the information about the salient features of the source image such as edges and lines. It can be inferred that the approximate coefficients of the decomposition level can be obtained from the approximate (low-frequency sub band) and detail (high-frequency sub bands) coefficients of the low level.

Therefore, it is necessary to develop an adaptive scheme for the fusion of source images which could re-strain the background information and enhance the information of changed regions in the great extent.), the wavelet coefficients high frequency is fused separately. The low-frequency sub- band, which represents the profile features of the source image, can significantly reflect the information of changed regions of two source difference 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. On the other hand, for high frequency sub bands, which indicate the information about the salient features of the source image such as edges and lines, the rule of minimum local area energy of wavelet co efficient is selected to suppress the background clutter. This rule is aimed at merging the homogeneous regions of the high-frequency portion from the mean-ratio image and the log-ratio image 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:

$$D_{LL}^{F} = \frac{D_{LL}^{m} + D_{LL}^{l}}{2}$$

$$D_{\epsilon}^{F}(i,j) = \begin{cases} D_{\epsilon}^{m}(i,j), & E_{\epsilon}^{m}(i,j) < E_{\epsilon}^{l}(i,j) \\ D_{\epsilon}^{l}(i,j), & E_{\epsilon}^{m}(i,j) \geq E_{\epsilon}^{l}(i,j) \end{cases}$$

Where, m and l represent the mean-ratio image and the log-ratio image, respectively. F denotes the new fused image DLL stands for low-frequency co-efficient. De (i, j) ($\in$= LH HL,HH) represents three high-frequency coefficients at point (i, j) in the corresponding sub images. The local area energy coefficient Ee(i, j) can be computed as follows:

Ee (i, j) = ΣkeNi,j[De(k)^2]

Where Ee (i, j) represents the local area energy of the wavelet coefficient at point (i, j) in the corresponding sub image, and represents the local window centered on (i, j). De (K) denotes the value of the wavelet coefficient that is around the local window .It should be noted that the proposed approach to generate the difference image is carried out in the multi resolution decomposition. Compared with the log-ratio image, the estimation of probability statistics model for the histogram of the fused difference image may be complicated since it incorporates both the log-ratio image information and the mean-ratio image in-formation at different resolution levels. Therefore, the thresholding technique, such as K&I and EM, may be un adapted 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. As can be seen from the above analysis, a classification method that is insensitive to the probability statistics model of histogram is needful to analyze the fused difference image.

C. Detect Changed Areas In The Fused Image Using The Improved FCM

The purpose to process the difference image is to discriminate changed area from unchanged area. In addition, clustering is a process for classifying objects or patterns in such a way that samples of the same cluster are more similar to one another than samples belonging to different clusters
Among the clustering methods, the FCM algorithm is one of the most popular methods since it can retain more information from the original image and has robust characteristics for ambiguity.

1) *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. This fuzzy factor can be defined mathematically as follows:

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d_{i,j+1}} \left(1 - u_{kj}\right)^m \|x_j - v_k\|^2$$

Where the ith pixel is the center of the local window, the jth pixel represents the neighboring pixels falling into the window around the ith pixel and d_k, i is the spatial Euclidean distance between pixels i and j. Represents the prototype of the center of cluster k and u_{ki} represents the fuzzy membership of the gray value j with respect to the k^{th} cluster.

By using the definition of Gki the objective function of the FLICM can be defined in terms of

$$J_m = \sum_{i=0}^{N} \sum_{K=1}^{c} [u_{ki}^{m} || X_i - V_k ||^2 + G_{ki}]$$

Where v_k represents the prototype value of the k^{th} cluster and v_{ki} represents the fuzzy membership of the ith pixel with respect to cluster k, N is the number of the data items, and c is the number of clusters. The foregoing analysis highlights the importance of the accurate estimation of the fuzzy factor G_{ki} to suppress effectively the influence of the noisy pixels. In addition, the local coefficient of variation is defined by

$$C_u = \frac{var\ (x)}{(\bar{x})^2}$$

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.

IV. Experimental Results

(A) Analyses Of Change Detection Results

The quantitative analysis of change detection results is set as follow. These criteria are from.

- First, we calculate the false negatives (FN, changed pixels that undetected).
- Second, we calculate the false positives (FP, unchanged pixels wrongly classified as changed).
- Third, we calculate the percentage correct classification (PCC). It is given by

PCC = (TP + TN) / (TP + FP + TN+ FN)

Here, TP is short for true positives, which is the number of pixels that are detected as the changed area in both the reference image and the result. TN is short for true negatives, which is the number of pixels that are detected as the unchanged area in both the reference image and the result.

Two experiments have been carried out, i.e., aimed at different purposes. The first experiment is aimed at the analysis of the effectiveness of the wavelet fusion strategy to generate the difference image. In addition, we compared the change detection performance of our algorithm with other two methods, including the mean-ratio operator and the log-ratio operator. In the second experiment, we analyzed the impact of the RFLICM algorithm onto the change detection results of the fused difference image. To verify the suitability of the proposed approach for the fused difference image, we presented comparative analysis of the performances of our proposed algorithm with that of the traditional FCM algorithm and the FLICM algorithm.

For accuracy assessment, kappa statistic, which is a measure of accuracy or agreement based on the difference between the error matrix and chance agreement, is reported to take into account of commission and omission errors. If the change detection map and the reference image are in complete agreement, then the kappa value is 1. If there is no agreement among the change detection map and the reference image, the kappa value is 0.

Table I: Change detection condition

Conditions	Mean-ratio	Log-Ratio	FLICM	RFLICM
TP	105993.0	10590.0	1565.00	102713.00
FP	1385.00	410.0	10600.00	0.00
FN	7.00	99.0	19.00	3287.00
TN	199.00	1174.00	1565.00	1584.00
Precision	0.99	1.00	0.01	1.00
Sensitivity	1.00	1.00	0.99	0.97
Specificity	1.00	0.74	0.99	1.00

Table II: PCC values obtained for difference Images

Difference Image	PCC
Mean-ratio	56%
Log-ratio	87%
FLICM	79%
RFLICM	98%

Table III: Calculation of accuracy

Difference Image	Accuracy
Mean-ratio	0.99
Log-ratio	1.00
FLICM	0.01
RFLICM	0.97

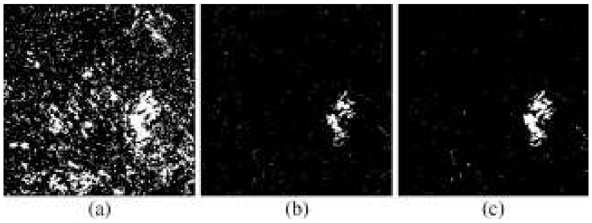

Fig. 2 Change detection results of the Bern data set based on the three difference images obtained by Otsu. (a) Based on the mean-ratio operator. (b) Based on the log-ratio operator. (c) Based on wavelet fusion

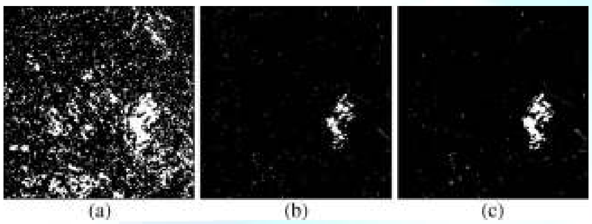

Fig. 3 Change detection results of the Bern data set based on the three difference images obtained by K-means. (a) Based on the mean-ratio operator. (b) Based on the log-ratio operator. (c) Based on wavelet fusion

As shown in Tables I, II and III, the change detection results of the fused difference image were compared with the ones generate from mean-ratio operator and log-ratio operator by Otsu and K-means, respectively. It can be seen from the analysis of the PCC that, the change detection results of mean-ratio difference image that achieved by both methods was disastrous. For the log-ratio operator, the PCC yielded was equal to 87% for Otsu, and 99.24% for K-means. And the proposed approach resulted in the highest PCC (99.35% for Otsu and 99.36% for K-means) and kappa (0.781 for Otsu and 0.784 for K-means). By a visual analysis of Figs. 2 and 3, we can have a better understanding of the behavior of the three different methods.

Figs. 2(a) and 3(a) depict the change detection results obtained from the mean-ratio image, which reveal that it has more spots than the other two methods because of the effect of the speckle phenomenon. As can be seen from Figs. 2(b) and 3(b), the change detection maps obtained from the log-ratio image have lesser spots because of the logarithmic transformation. However, it also caused the loss of information in changed areas since the operation of log-ratio may abate the high-intensity pixels. The change detection maps yield from the wavelet fusion image are shown in Figs. 2(c) and 3(c).

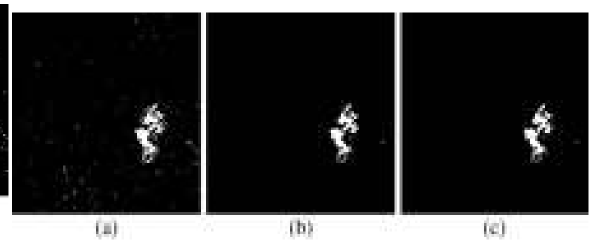

Fig. 4. Change detection results of the Bern data set achieved by (a) FCM, (b) FLICM, and (c) Proposed RFLICM.

Table IV: Comparison of the Change Detection results on the Bern Data Set Acquired by the FCM, FLICM, and RFLICM

Method	FP	FN	PCC	Kappa
FCM	507	61	99.37%	0.790
FLICM	137	169	99.66%	0.867
RFLICM	133	159	99.68%	0.871

To assess the impact of RFLICM algorithm on the results of SAR-image change detection which based on the wavelet fusion difference image, in the second experiment, a comparison was carried out among traditional FCM, FLICM and RFLICM. As shown in Fig. 4(a), the change detection map achieved by traditional FCM contains lots of spots. This is explained by the fact that it fail to consider any information about spatial context. By contrast, by incorporating the local information, the change detection maps generated by FLICM, this is indicated In figure 4(b) and RFLICM in fig 4(c) were robust to the outliers. As shown in Table IV, it depicts the behavior of kappa, PCC, FP and FN among these three methods. The PCC yielded by RFLICM, FLICM and FCM were equal to 99.68%, 99.66% and 99.37%, respectively. RFLICM outperforms FLICM and FCM obviously.

V. CONCLUSION

In this paper, 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 proposed, the key idea is to restrain the background (unchanged areas) information and to enhance the information of changed regions in the greatest extent. The information of background obtained by the log-ratio image is relatively flat on account of the logarithmic transformation. Second, in contrast with the log-ratio image and the mean-ratio image, the estimation of the probability statistics model for

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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. 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 FLICM algorithm that incorporates both local spatial and gray information is proposed, which is relatively insensitive to probability statistics model. The FLICM algorithm introduces the reformulated factor as a local similarity measure to make a tradeoff between image detail and noise.

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