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DWT Based Image Fusion & RFLICM Clustering For Effective Change Detection In Synthetic Aperture Radar Images

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Abstract

This paper mainly focuses on Image Fusion and Fuzzy clustering for effective change detection in Synthetic Aperture Radar (SAR) images de-noised through SRAD filter. SAR image is commonly affected by Speckle noise, it is reduced by anisotropic diffusion filter. In the presence of speckle noise reducing by anisotropic diffusion excels over the traditional speckle removal filter. Then the image fusion technique is used to produce a difference image from input images. A fuzzy C- means clustering algorithm is proposed for classification of changed and unchanged regions in the fused image.

Index Terms- Clustering, Fuzzy C-means (FCM) Algorithm, Image Change Detection, Image Fusion, Synthetic Aperture Radar (SAR).

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1. INTRODUCTION

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 images [1]. In the last decades, it has attracted widespread interest due to a large number of applications in diverse disciplines such as remote sensing [2]-[7], medical diagnosis, satellite image processing 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.

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time incidents. It involves he ability to quantify temporal effects using multi temporal data sets. There is a definite need for a change detector which will automatically correlate and compare two sets of imagery taken of the same area at different time incidents and display the changes and their locations to the interpreter. It has been suggested that a significant increase in speed can be achieved for image processing by representing only the changes rather than expose the human viewer to all the information in both images. There are different types of classification. They are as follows Supervised and Unsupervised.

The main steps of supervised change detection is: 1)The identity and location of some of the land cover types are known a priori through a combination of fieldwork, air photo interpretation and personal experience. The image analyst “supervises” the pixel categorization process by specifying for a computer algorithm, numerical descriptors of various land cover types in a scene. The image analyst guides the classification by identifying areas on an image that are known to belong to given categories (calibration of decision rules).

Unsupervised change detection in SAR images can be divided into three steps: 1) image preprocessing like noise removal; 2) producing difference image between the multitemporal input images; and 3) analysis of the difference image. The tasks of the first step mainly include co registration, geometric corrections, and noise reduction. In image processing and computer vision, anisotropic diffusion is a technique used to reducing speckle noise without affecting significant parts of the image content. Anisotropic diffusion process is a linear process and space-invariant transformation of the original images.

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 between the considered couple of temporal images. 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, 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 not effective to calibration errors[11]. In third step, changes are classified by applying the fuzzy clustering.

In general, it appears clearly from the literature that 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, 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.

2. METHODOLOGY

In this section, we focus on describing the proposed change detection approach, which is composed of two main steps:1) Generate the difference image based on image fusion using DWT, and 2) detect changed areas in the fused image using the RFLIFCM.

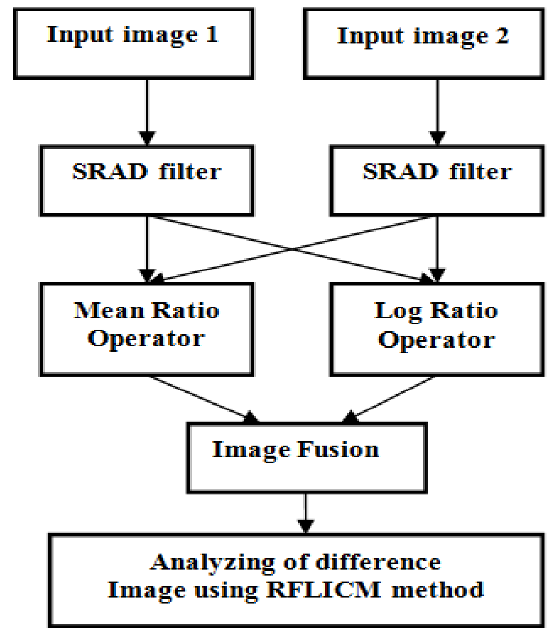

Figure 1.Flowchart of the proposed change detection approach.

2.1. 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, multiscale transforms, such as the discrete wavelet transform (DWT), curvelets, contourlets, 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 curvelets and contourlets are proved to have a better shift invariance property and directional 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

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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. As mentioned in the previous section, 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

$$X_m = 1 - \min\left(\frac{u1}{u2}, \frac{u2}{u1}\right)$$

$$X_l = | \log x_2 - \log x_1 |$$

where u1and u2 represent the local mean values of multitemporal SAR images x1 and x2, respectively. The ratio difference image is usually expressed in a logarithmic or a mean scale because of the presence of speckle noise.

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 may emphasize the differences in the low intensities of the temporal images. 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 project. The information of changed regions reflected by the mean-ratio.

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 curvelets and contourlets are proved to have a better shift invariance property and directional selectivity. However, their computational complexities are obviously higher than the DWT.

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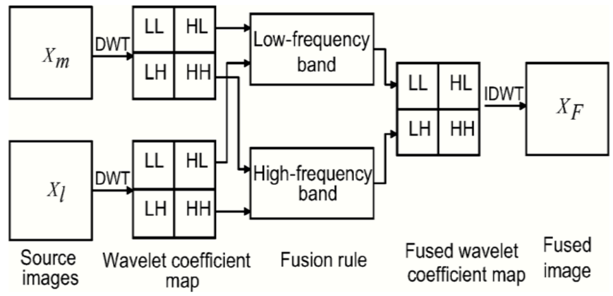

Figure 2.Process of image fusion based on DWT.

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. As mentioned in the previous section, the two source images used for fusion are obtained from the mean-ratio operator and the log-ratio operator. 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.

2.2. Detect Changed Areas in the Fused Image Using the Improved FCM algorithms

2.2.1. 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. In particular, a novel fuzzy factor is introduced into the object function of FLICM to enhance the clustering performance. This fuzzy factor can be defined mathematically as follows

$$G_{ki} = \sum_{j \in Ni} \frac{1}{dij+1} (1-u_{kj})^m \, \| x_j - v_k \|$$

where the i th pixel is the center of the local window, the i th pixel represents the neighboring pixels falling into the window around the i th pixel, and is the spatial

Euclidean distance between pixels and. Represents the prototype of the center of cluster, and G_{ki}represents the fuzzy membership of the gray value with respect to the i^{th} cluster.

It can be seen that factor is 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 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. In general, with the application of the fuzzy factor , 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.

2.2.2. Proposed RFLICM Method. RFLICM is based on the analysis of the fuzzy factor Gki, it can be inferred that the local gray-level information and spatial information in Gki are represented by the gray-level difference and spatial distance, respectively. Furthermore, the local spatial relationship changes adaptively according to spatial distances from the central pixel.

The authors of FLICM attempt to measure the damping extent of the neighbors with the spatial distances from the central pixel. For the neighborhood pixels with the same gray-level value, the greater the spatial distance is, the smaller the damping extent is, and vice versa. However, the spatial distance used to measure the damping extent of the neighbors may be unreasonable in some cases. The foregoing analysis highlights the importance of the accurate estimation of the fuzzy factor to suppress effectively the influence of the noisy pixels.

In order to overcome the shortcoming mentioned above, in this paper, the local coefficient of variation is adopted to replace the spatial distance. 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 C_u reflects the gray-value homogeneity degree of the local window.

It exhibits high values at edges or in the area corrupted by noise and produces low values in homogeneous regions. If the neighbor pixel and the central pixel are located in the same region, such as the homogeneous region or the area corrupted by noise, the results of the local coefficient of variation obtained by them will be very close and vice versa. In general, compared with the spatial distance, the discrepancy of the local coefficient of variation between neighboring pixels and the central pixel is relatively accordance with the gray-level difference between them. In addition, it helps to exploit more local context information since the local coefficient of variation of each pixel is computed in a local window. Here, the modified fuzzy factor can be defined as

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

where C_u is the local coefficient of variation of the central pixel, $C_u{}^j$ represents the local coefficient of variation of neighboring pixels, and C_u is the mean value of $C_u{}^j$ that is located in a local window.

As shown in above equation, the reformulated factor G_{ki}' balances the membership value of the central pixel taking into account the local coefficient 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}'

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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 preexistence.

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

Step 1) Set values for c,m , ε and .
Step 2) Initialize the fuzzy partition matrix and set the loop counter b=0.
Step 3) Calculate the cluster prototypes.
Step 4) Compute the partition matrix using (8).
Step 5) $\max\{U^{(b)} - U^{(b+1)}\} < \varepsilon$ then stop; otherwise, set b= b+1 , and go to step 3).

3. RESULT ANALYSIS

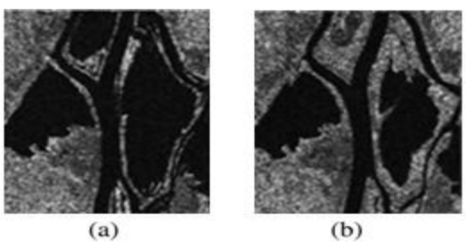

Figure 3.Multitemporal images relating to Ottawa used in the experiments.
(a) Image acquired in July 1997 during the summer flooding.
(b) Image acquired in August 1997 after the summer flooding.

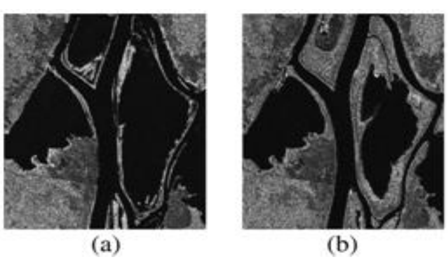

Figure 4.SRAD filter output.
(a) SRAD output of first input image
(b) SRAD output of second input image

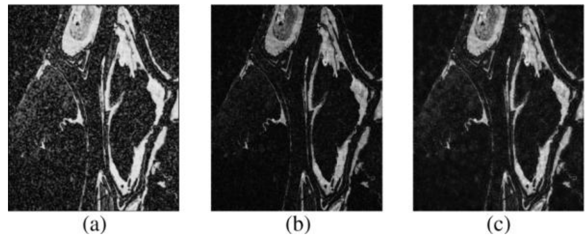

Figure 5.Difference images of the Ottawa data set generated from
(a)mean-ratio operator,
(b) log-ratio operator,
(c) wavelet fusion.

Figure 6.Change detection results of Ottawa data set achieved by
(a) FCM,
(b) FLICM,
(c) Proposed RFLICM.

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4. CONCLUSION

In the present work, 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, SRAD filter highly reduced speckle noise. Second for the wavelet fusion approach key idea is to restrain the background (unchanged areas) information and to enhance the information of changed regions in the greatest extent. 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). Third, 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 changed information more exactly.

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