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Robust Technique for Change Detection in Multitemporal Synthetic Aperture Radar Images

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Abstract— This paper presents an unsupervised distribution free change detection for Synthetic Aperture Radar (SAR) images based on an image fusion strategy and novel fuzzy clustering algorithm. Here we first perfom the mean ratio and log ratio on two original images and then apply DWT based fusion rules for performing image fusion and apply RFLICM and FLICM techniques for DWT based fused image. The image fusion technique is introduced to generate a difference image by using complementary information by performing log ratio and mean ratio on two original images and by applying DWT based fusion rules. Since the SAR images suffer from the speckle noise, so thatht's why we proposed an unsupervised distribution-free change detection approach for Synthetic Aperture Radar images based on an image fusion strategy and novel fuzzy clustering algorithm. A reformulated fuzzy local instruction C- means (RFLICM) clustering algorithm is proposed for classifying changed and unchanged regions in the fused difference image. 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 better performance. The change detection results obtained by the improved fuzzy clustering algorithm exhibited lower error than its preexistences.

Key Words— Change detection, Clustering, DWT, FLICM, Image fusion, RFLICM, Synthetic Apertutre Radar (SAR).

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1 Introduction

CHANGE DETECTION:
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. Change-detection techniques have been used successfully in many applications, such as environmental monitoring, study on land-use/land-cover dynamics, analysis of forest or vegetation changes, damage assessment, agricultural surveys, and analysis of urban changes [1] [2]. 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 [2].

The "multitemporal" SAR images are three-dimensional (3-D) datasets with two axes corresponding to the conventional spatial domain and the third axis to the temporal direction. Most of the sought-after information is located in transition areas where the contrast or the texture differences in the radiometry reveal temporal changes and spatial features.

"Temporal changes" correspond to physical changes that may occur on the ground surface and can be observed in the variations of the SAR backscattering coefficient. ***"Spatial features"*** correspond to point-targets such as buildings, linear features such as roads or thin rivers, and borders of surface features such as lakes, large rivers, etc. These features introduce spatial discontinuities that are difficult to detect in the presence of speckle when only a single image is available. The multitemporal SAR data are useful to improve their detection [3].

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 by 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 non-robust to calibration errors.

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, 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 [4], which is insensitive to noise, to identify the change areas in the difference image, without any distribution assumption.

2 Literature Survey

2.1 Image Change Detection Algorithms

Detecting regions of change in multiple images of the same scene taken at different times is of widespread interest due to a large number of applications in diverse disciplines,

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including remote sensing, surveillance, medical diagnosis and treatment, civil infrastructure, and underwater sensing. This paper presents a systematic survey of the common processing steps and core decision rules in modern change detection algorithms, including significance and hypothesis testing, predictive models, the shading model, and background modeling. We also discuss important preprocessing methods, approaches to enforcing the consistency if the change mask, and principles for evaluating and comparing the performance of change detection algorithms. It is hoped that our classification of algorithms into a relatively small number of categories will provide useful guidance to the algorithm designer.

2.2 A Detail-Preserving Scale-Driven Approach to Change Detection in Multitemporal SAR Images

The proposed approach exploits a wavelet-based multiscale decomposition of the log-ratio image (obtained by a comparison of the original multitemporal data) aimed at achieving different scales (levels) of representation of the change signal. Each scale is characterized by a different tradeoff between speckle reduction and preservation of geometrical details. For each pixel, a subset of reliable scales is identified on the basis of a local statistic measure applied to scale-dependent log-ratio images. The final change detection result is obtained according to an adaptive scale-driven fusion algorithm. Experimental results obtained on multitemporal SAR images acquired by the ERS-1 satellite confirm the effectiveness of the proposed approach.

2.3 Modeling SAR Images with a Generalization of the Rayleigh Distribution

Due to the physics of the radar imaging process, SAR images contain unwanted artifacts in the form of a granular look which is called speckle. The assumptions of the classical SAR image generation model lead to a Rayleigh distribution model for the histogram of the SAR image. However, some experimental data such as images of urban areas show impulsive characteristics that correspond to underlying heavy-tailed distributions, which are clearly non-Rayleigh. This paper presents the amplitude distribution of the complex wave, the real and the imaginary components of which are assumed to be distributed by the -stable distribution, is a generalization of the Rayleigh distribution. The amplitude distribution is a mixture of Rayleigh's as is the k-distribution in accordance with earlier work on modeling SAR images which showed that almost all successful SAR image models could be expressed as mixtures of Rayleigh's. Also present parameter estimation techniques based on negative order moments for the new model. Finally, the performance of the model on urban images is compared with other models such as Rayleigh, Weibull, and the k-distribution.

2.4 Change Detection in Multisensor SAR Images Using Bivariate Gamma Distributions

This project studies a family of distributions constructed from multivariate gamma distributions to model the statistical properties of multisensor synthetic aperture radar (SAR) images. These distributions referred to as multisensory multivariate gamma distributions (MuMGDs) are potentially interesting for detecting changes in SAR images acquired by different sensors having different numbers of looks. The first part of this paper compares different estimators for the parameters of MuMGDs. These estimators are based on the maximum likelihood principle, the method of inference function for margins, and the method of moments. The second part of the paper studies change detection algorithms based on the estimated correlation coefficient of MuMGDs. Simulation results conducted on synthetic and real data illustrate the performance of these change detectors.

3 OBJECTIVES

- The main objective is analyzing SAR images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates. Then perform image fusion and apply Fuzzy logic for clustering.
- For the remote sensing images, diffrencing (subtracttion operator) and rationing (ratio operatot) are well known techniques for producing a difference image. In 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 non-robust to calibration errors.
- Perform image fusion to generate the difference image by using complementary information from the mean-ratio and the log-ratio image.
- The goal of image fusion is to minimize artifacts or distortion in the composite image as a result of fusion.
- A reformulated fuzzy local-information C-means (RFLICM) clustering algorithm is proposed for classifying changed and unchanged regions in the fused difference image.

4 CHANGE DETECTION TECHNIQUES

4.1 Clustering

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.

4.2 Fuzzy C-Means Clustering

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.

4.3 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 Gki is introduced into the object function of FLICM to enhance the clustering performance. This fuzzy factor can be defined mathematically as follows:

$$G_{ki} = \sum_{i \in N_i} 1/d_{ii} + (1-u_{ki})^m \, \|x_i - v_k\|^{-} \tag{1}$$

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 dij is the spatial Euclidean distance between pixels i and j. V_k represents the prototype of the center of cluster k , and ukj represents the fuzzy membership of the gray value j with respect to the kth cluster. It can be seen that factor is Gki 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, it 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 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.

5 Proposed Methodology

5.1 Module Names

- Ratio Difference Image
- Image Fusion using DWT algorithm

5.2 Module Description

Ratio Difference Image: The 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; this detector assumes that a change in the scene will appear as a modification of the local mean value of the image. Both methods have yielded effective results for the change detection in SAR imagery but still have some disadvantages: The logarithmic scale is characterized by enhancing 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 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. In general, the underlying idea of the optimal difference image is that unchanged pixels exhibit small values, whereas changed areas exhibit larger values. That is to say that 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. 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;

$$Xm = 1 - \min(\mu1/\mu2, \mu2/\mu1) \tag{2}$$

$$Xt = \| \log X2/X1 \| = \| \log X2 - \log X1 \| \tag{3}$$

Where μ1 and μ2 represent the local mean values of multi temporal SAR images X1 and X2 respectively.

Image Fusion: Image Fusion allows one to combine images in a variety of ways. An effective image fusion algorithm should integrate all the relevant information as much as possible.

The objectives of the image fusion are the following:

i. To combine complementary information from images obtained from a variety of different sensors or from the same sensors.
ii. To develop novel ways to use multi sensor, multi resolution, multi spectral imagery from airborne, space borne, ship board or ground-based platform.

The goal of image fusion is to minimize artifacts or distortion in the composite image as a result of fusion. With the rapid growth of advance image processing methodology and availability of variety of sensors, the idea of combining images has become important and has emerged as a new promising research area. A large variety of applications of image fusion is seen in Geo science and remote sensing application where satellite images from different bands and at different resolution is combined to extract more useful information of ground terrain. Important defense related applications in image fusion are in change detection, where images acquired over a period of time are fused to detect changes. With rapid advancement of medical research, increasing demand of using imaging research for medical diagnosis and availability of multimodal medical imagery for clinical application, the idea of combining images from different modalities becomes very important and medical image fusion has emerged as a new and promising research area.

6 Generate 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 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.

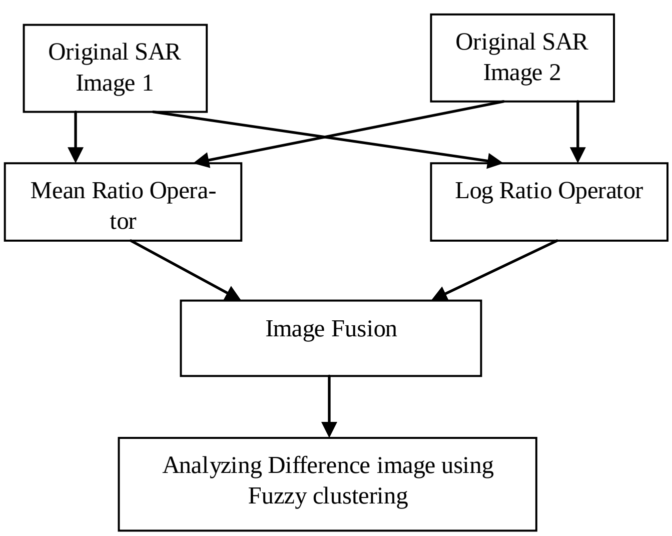

Fig. 1: Flowchart of the proposed change detection approach

As mentioned in the previous module, 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,

$$X_m = 1 - \min(\mu_1/\mu_2, \mu_2/\mu_1) \quad (4)$$

$$X_t = \| \log X_2/X_1 \| = \| \log X_2 - \log X_1 \| \quad (5)$$

Where μ1 and μ2 represent the local mean values of multi temporal SAR images X1 and X2 respectively.

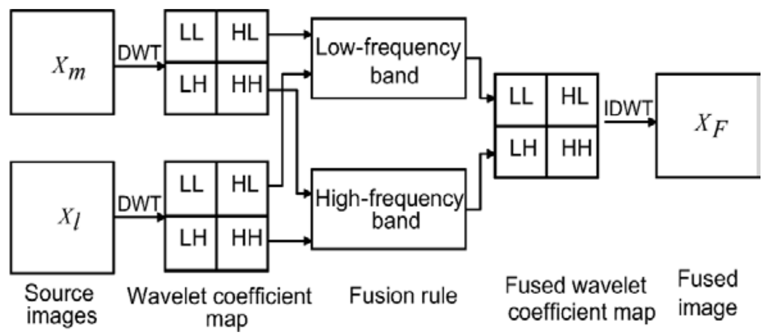

Fig.2: Process of Image Fusion based on DWT

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 multiresolution decomposition of each source image. Then, we fuse corresponding coefficients of the approximate and detail subbands 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 multiresolution representation to obtain the fused result image. Fig. 2 shows the process of the proposed image fusion based on the DWT. Here, Xm and Xl 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. 2, each source image is decomposed into four images of the same size after one level of decomposition. The low-frequency subband XLL1, which is called the approximation portion, represents the profile features of the source image. Three high-frequency subbands XLH1 XHL1 andXHH1 , 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 kth decomposition level can be obtained from the approximate (low-frequency subband) and detail (high-frequency subbands).

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:

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$$D^{F}_{LL} = D^{m}_{LL} + D^{l}_{LL} \qquad /2 \qquad (6)$$

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.

7 RESULT

The unsupervised distribution free change detection approach for synthetic aperture radar (SAR) images based on an image fusion strategy and a novel fuzzy clustering algorithm is carried out and verified and the output results have been obtained as follows:

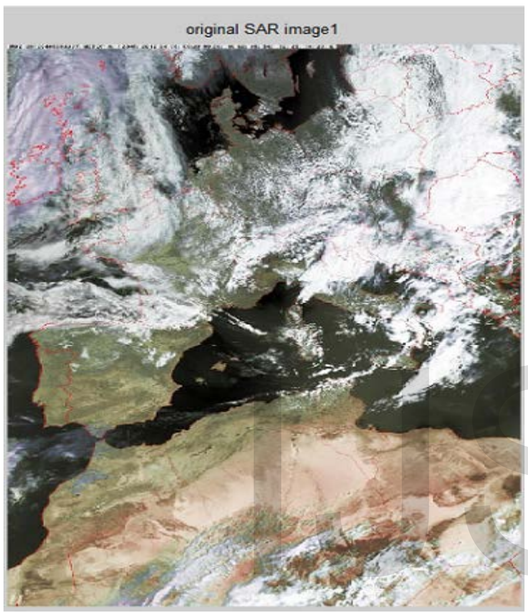

Fig. 3: Original SAR Image 1

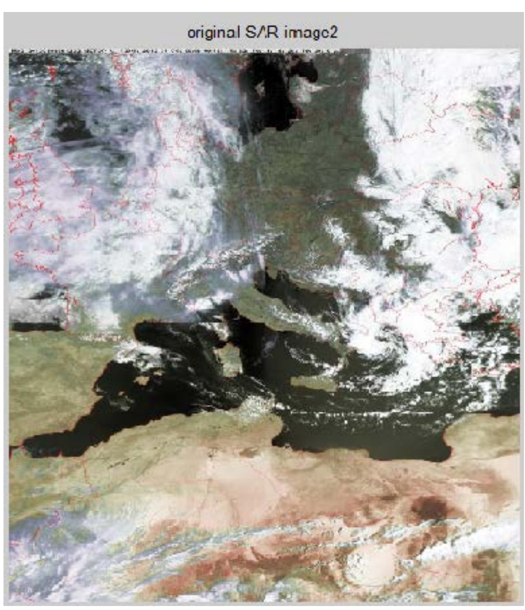

Fig. 4: Original SAR Image 2

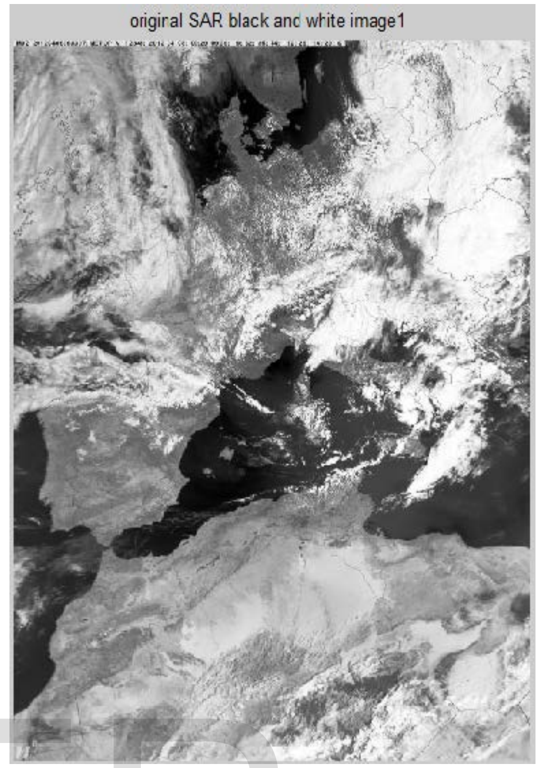

Fig. 5: Original SAR black and white image 1

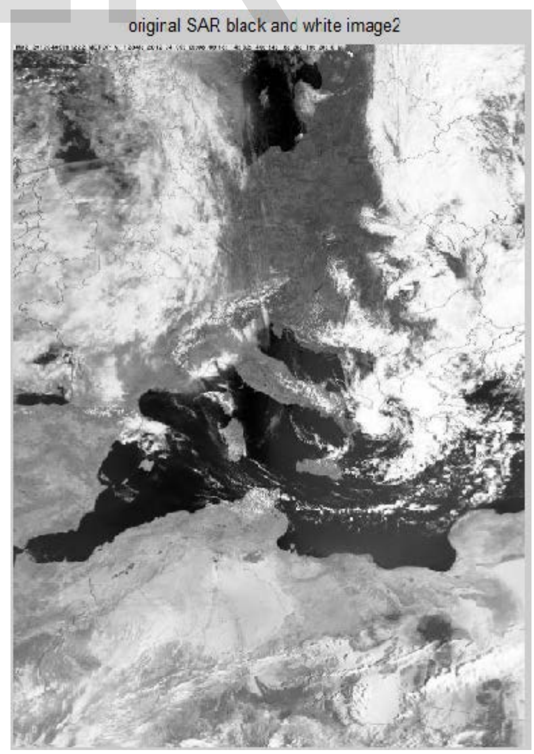

Fig. 6: Original SAR black and white image 2

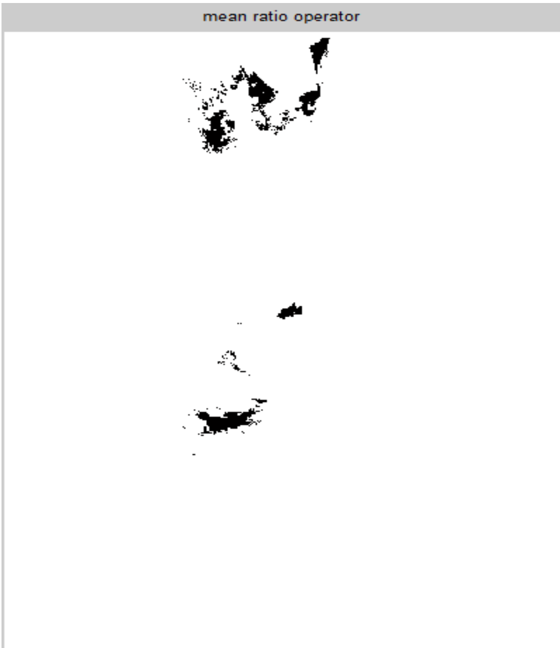

Fig. 7: Mean Ratio Operator

Fig. 9: DWT based Fused Image

Fig. 8: Log Ratio Operator

Fig. 10: Ground Truth Image

Fig. 11: FLICM Output Image

Fig. 12: RFLICM Output

8 Conclusion

Here, it has been presented a novel SAR-image change detection approach based on image fusion. For the wavelet fusion approach, 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).

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