



# An Effective Framework for Change Detection in SAR Images Based On Image Fusion and Compressed Projection

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**ABSTRACT:** The proposed system develops a novel approach for change detection in multi temporal synthetic aperture radar (SAR) images. The approach classifies changed and unchanged regions by Fuzzy C means clustering algorithm with a novel Markov random field (MRF) energy function. In order to reduce the effect of speckle noise and the complex mixture of terrain environment, this paper presents a novel unsupervised change detection method based on image fusion strategy and compressed projection. First, a Gauss-log ratio operator is proposed to generate a difference image. In order to obtain a better difference map, image fusion strategy is applied using complementary information from Gauss-log ratio and log ratio difference image. Second, non sub-sampled contourlet transform (NSCT) is used to reduce the noise of the fused difference image, and compressed projection is employed to extract feature for each pixel. Experiment results show that the proposed method is effective for SAR image change detection in terms of shape preservation of the detected change portion and the numerical results.

**KEYWORDS:** FCM clustering, image change detection, Markov random field (MRF), synthetic aperture radar (SAR).compressed projection, image fusion, non sub-sampled contourlet transform (NSCT).

## I.INTRODUCTION

Change detection in SAR images is the process of the analysis of two co-registered SAR images that are acquired over the same geographical area at different times. Such analysis is unsupervised when it aims to discriminate between two opposite classes (which represent unchanged and changed areas) with no prior knowledge about the scene [1]. The proposed system comprises a basic aspect of different application areas like geographical monitoring, medical science, infrastructural development, military operations, positioning and hazard assessment of earthquake area, monitoring of crop growth conditions, detecting of urban land use etc. [2]. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Synthetic aperture radar (SAR) is active microwave coherent imaging radar, so it can acquire remote sensing data under all weather and all day, which can make up for the shortage of optics and infrared remote sensing. Due to involvement of large areas in analysis, it is necessary to develop automated techniques so as to reduce manual effort in image analysis [3] and there are many SAR image change detection algorithms have been proposed for this.

In order to reduce the effect of speckle noise and the complex mixture of terrain environment the system proposes change detection method based on image fusion strategy and compressed projection. Here, Gauss-log ratio operator is proposed to obtain a stable and clear difference map. In order to make better use of the Gauss-log ratio operator and log-ratio operator, we introduce a fusion strategy to generate a fused difference image based on discrete wavelet transform (DWT). In order to reduce the noise in the fused difference image and improve the performance of the subsequent clustering or classification, NSCT model is used to suppress noise of the image and keep shape of the changed portion. Finally, the projected system uses the simple MRF (Markov Random Field) FCM clustering to obtain the change detection map.

## II.METHODOLOGY

Change detection in SAR images generally consists of two steps: 1) generation of a difference image using different kinds of operators and 2) unsupervised or supervised classification of the image into two change and no-change classes. The ratio operator is the most widely used technique to obtain a difference image [4], the ratio operator is robust to calibration and radiometric errors. In addition, considering the multiplicative nature of speckle in SAR images, the log-ratio operator is often used to generate a difference image, which can reduce the influence of speckle noise theoretically.

The process of change detection includes the generation of the DI and the analysis of it. Let us consider two co-registered SAR images:  $X_1 = \{I_1(h, l), 1 \leq h \leq A, 1 \leq l \leq B\}$ , and  $X_2 = \{I_2(h, l), 1 \leq h \leq A, 1 \leq l \leq B\}$ . Both of them are of size  $A \times B$  and are acquired by an SAR sensor over the same geographical area at two different times  $t_1$  and  $t_2$ . Then, the conventional log-ratio operator is applied to generate a DI, which is denoted by  $I_X = \{I_X(h, l), 1 \leq h \leq A, 1 \leq l \leq B\}$ .

We aim at producing a change map that represents changes between the acquisition dates of the two images  $X_1$  and  $X_2$ . The entire algorithm for unsupervised change detection in SAR image based on Gauss log ratio image fusion and compressed projection contains five parts: 1) producing the difference maps via Gauss-log ratio and log ratio operators; 2) image fusion via DWT; 3) image de-noising via NSCT; 4) feature extraction via compressed projection; and 5) the change map obtained by using MRFFCM clustering to generate two clusters, as shown in Fig. 1.

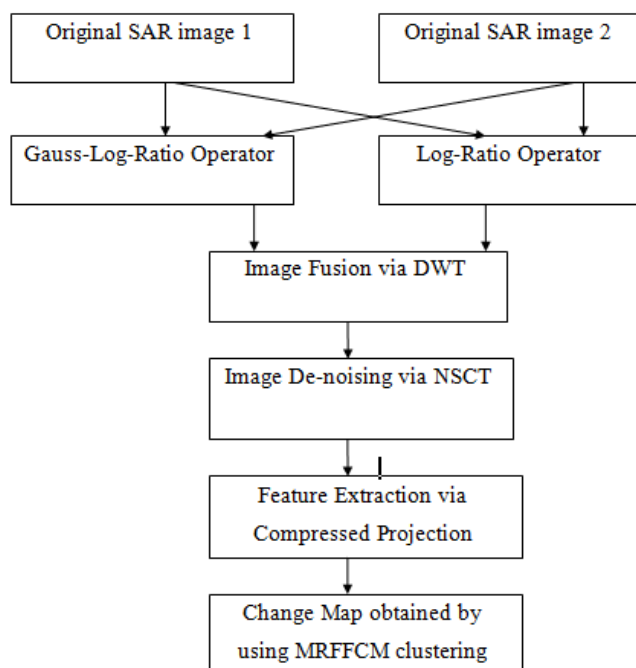


Fig. 1 Flow Chart for the Proposed Change Detection Approach

## III. ALGORITHM FOR CHANGE DETECTION IN SAR IMAGES

STEP1. Producing the Difference Image via Gauss-Log Ratio and Log Ratio Operators

The ratio operator is widely used to obtain a difference image. The commonly used Log-ratio operator converts the linear scale of SAR data to a logarithmic scale before the differencing operation, and thus transforms the multiplicative



noise into additive noise. In order to enhance the real change trend as well as suppress the unchanged portions in the difference image and preserve the homogeneity of the changed portions, the Gauss-log ratio operator is proposed in this paper, which considers the relationship between the intensities of local patches of multi temporal images.

#### STEP2. Image Fusion via DWT

In order to obtain a better difference image, we fuse the information of the difference image. Here, the “better” means the difference image is of greater contrast between the changed and unchanged portions and of the homogeneity in the changed one, which can improve the accuracy of the subsequent clustering or classification. Image fusion refers to a process of combining relevant information from two or more images into a fused image that possesses more information than any of the input images [6], [7]. Wavelet transform overcomes the defect of the poor correlation between the adjacent scale image information and fully reflects local variation of the original image [24], [25]. Since DWT has lower computational complexities, we also use the DWT for image fusion in this paper.

#### STEP3. Image De-noising via NSCT

NSCT has the characteristics of multi-resolution, localization, directionality, anisotropy, and shift-invariant [9]. It can sufficiently capture the geometrical details of the image and keep the object information and the edge well. This paper utilizes log-ratio operator to transform multiplicative noise into additive one. In order to make the change map possess more complete edge and contour, it is feasible to use NSCT to reduce the noise of the fused difference image.

#### STEP4. Feature Extraction via Compressed Projection

Compressed projection (also known as random projection) has recently emerged as a surprisingly useful tool in signal processing [8]. The compressed projection can preserve the relevant structure in a signal when the signal is projected onto a small number of random basis functions. Although some information may be lost through such a projection, this information tends to be incoherent with the relevant structure in the signal. That is to say, a small number of compressed vectors obtained by compressed projection contain enough information to preserve the underlying local texture structure. In this sense, compressed projection is a universal measurement tool. Another benefit is that compressed projection can provide dimensionality reduction, which can greatly reduce the amount of data to be processed. In this paper we use the compressed projection to extract the feature vector of each pixel in the de-noised difference image

### IV. MAIN PROCEDURE OF MARKOV RANDOM FIELD FUZZY C-MEANS CLUSTERING

In general, an image  $I = \{I(h, l), 1 \leq h \leq A, 1 \leq l \leq B\}$  itself can be viewed as a field, and each pixel of image is an element. If and only if some property of each element is only related to the neighborhood ones and is of no relationship to the other ones in the field, system call the random field  $p(x)$  an MRF. To emphasize the concept, let  $\partial$  be a neighborhood system lying on the field, and then, the previously considered random field  $p(x)$  is an MRF with respect to the introduced neighborhood system  $\partial_j$  if [5]

$$p(x_j | x_{I-\{j\}}) = p(x_j | x_{\partial_j}) \quad (1)$$

where  $j = (h, l)$  denotes the position of a certain element in the field, and  $x_{I-\{j\}}$  means the property of the whole elements in the field except the pixel  $j$ . Figure given below is used to illustrate the concept.

The proposed MRFFCM improves FCM by modifying the membership of each pixel according to the MRF-based spatial context. The spatial context is contained in the pivotal energy function through the use of the neighborhood system. The energy function is established, and then, the Gibbs expression in (2) is computed to generate the so-called point wise prior probability before up- dating the membership, and thus, the aim to deal with spatial context is reached by adding the MRF into FCM.

The main procedure of MRFFCM is as follows.



- In the first iteration ( $k = 1$ ), derive the mean  $\mu_i^1$  and the standard deviation  $\sigma_i^1$  of the two classes through the K&I method. In addition, the initial membership matrix  $\{u_{ij}^1\}$  is generated by utilizing the original FCM algorithm unmodified ( $I = u, c$ ). Then by means of hard division generate same kind number matrix  $\{n_{i \in c_j}\}$ , and each element of the matrix denotes the number of the neighborhood pixels belonging to  $i$ .
- In the  $k^{\text{th}}$  iteration, establish the energy matrix  $\{E_{ij}^k\}$ . This step is the key step to utilize the spatial context.
- Using Gibbs expression, compute the point wise prior probabilities of the MRF, and get the point wise prior probability matrix  $\{\pi_{ij}^k\}$ .

$$\{\pi_{ij}^k\} = \frac{\exp(-E_{ij}^k)}{\exp(-E_{uj}^k) + \exp(-E_{cj}^k)} \quad (2)$$

- Compute the conditional probability  $\{p_i^k\}$  that is given by (3.5), shown below, and then, generate the distance matrix  $\{d_{ij}^k\}$  that is given by (3.6), shown below:

$$p_i^k \left( (y_i | \mu_i^k, \sigma_i^k) \right) = \frac{1}{\sigma_i^k \sqrt{2\pi}} \exp \left[ -\frac{(y_i - \mu_i^k)^2}{2(\sigma_i^k)^2} \right] \quad (3)$$

- Compute the objective function  $J_{ij}^k$  that is given by (3.6), shown below, where  $I_X$  denotes the DI generated by the log-ratio operator. In case of convergence (which is presented in (3.7), shown below, where  $\delta$  is the convergence threshold), exit and output  $\{U_{ij}^k\}$ ; otherwise, go to step 6. It is worth noting that in existing system, another objective function with an artificial parameter is used. Conceive that function, but find it hard to search for an appropriate value of the parameter. Therefore, the original FCM objective function is used.

$$J_{ij}^k = \sum_{i=u,c} \sum_{j \in I_X} (u_{ij}^k)^2 (d_{ij}^k)^2 \quad (4)$$

$$\left| J_{ij}^k - J_{ij}^{k-1} \right| \leq \delta \quad (5)$$

- Compute the new membership that is given by (3.8), generating the new membership matrix  $\{U_{ij}^{k+1}\}$ , which is to be used in the next iteration process.

$$U_{ij}^{k+1} = \frac{\pi_{ij}^k \exp(-d_{ij}^k)}{\pi_{uj}^k \exp(-d_{uj}^k) + \pi_{cj}^k \exp(-d_{cj}^k)} \quad (6)$$

- Update the mean and the standard deviation as  $\mu_i^{k+1}$  and  $\sigma_i^{k+1}$ , update  $k = k + 1$ . Then, return to step 2.

## V. RESULTS AND DISCUSSION

In this proposed system, a novel change detection approach specifically toward the analysis of multi temporal SAR images has been presented. This approach is based on the universal utilized FCM algorithm and the MRF model. After generating the DI through the log-ratio operator, add the MRF method in the procedure of FCM.

Change detection is a process that analyzes images acquired on the same geographical area at different times to identify changes that may have occurred.

The objective of the proposed system is aiming at producing a difference image that represents the change information between the two times; then, a binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged

In order to validate the effectiveness of the proposed unsupervised change detection in SAR image based on Gauss-log ratio image fusion and compressed projection, different images of the same scene taken at different times are chosen for experiments to show the performance of the proposed method.

Fig. 2 shown below is the image acquired by the remote sensing SAR satellite in April 1975.

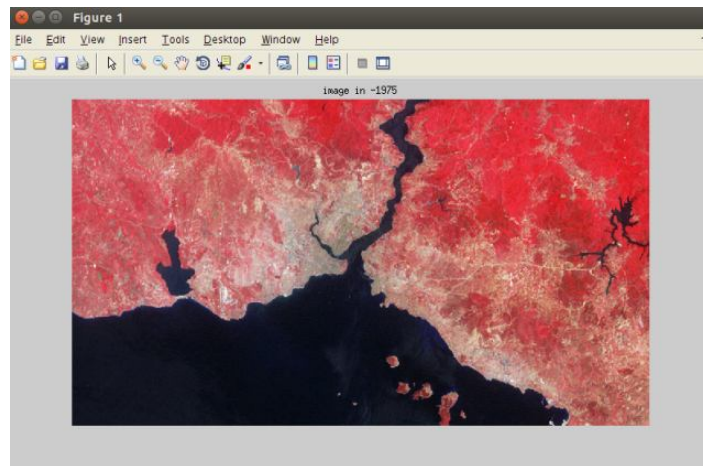


Fig. 2 Original SAR Image Acquired in 1975

Fig. 3 given below is the image acquired by remote sensing synthetic aperture radar in 2011.

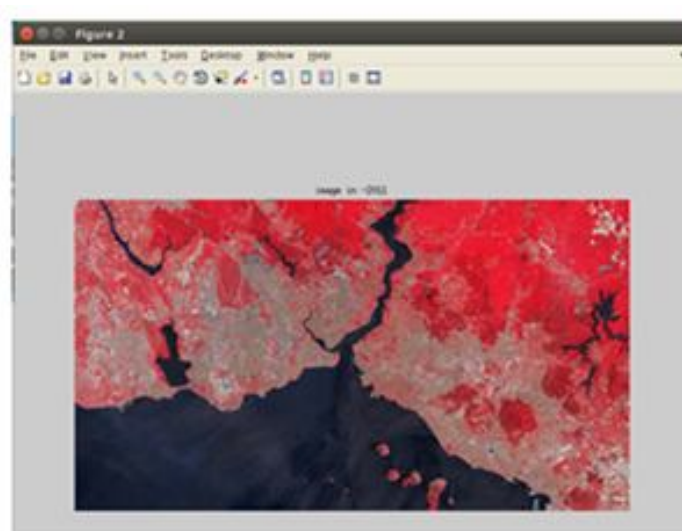


Fig. 3 Original SAR Image Acquired in 2011

Geometric correction and registration are usually implemented to align the above two images in the same coordinate frame.



As shown in the Figure 4 in order to reduce the burden of computation, the grey scales of original image should be adjusted. Computation will bring some difficulties. For a SAR image grey levels are adjusted to 8 or 16 and it doesn't damage texture information.

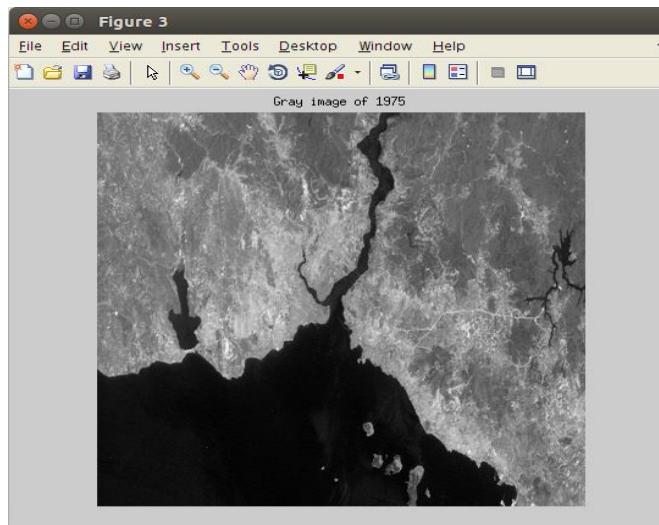


Fig. 4 Gray Scale Image of 1975

As shown in Fig. 5 it shows the gray scale image acquired in 2011.

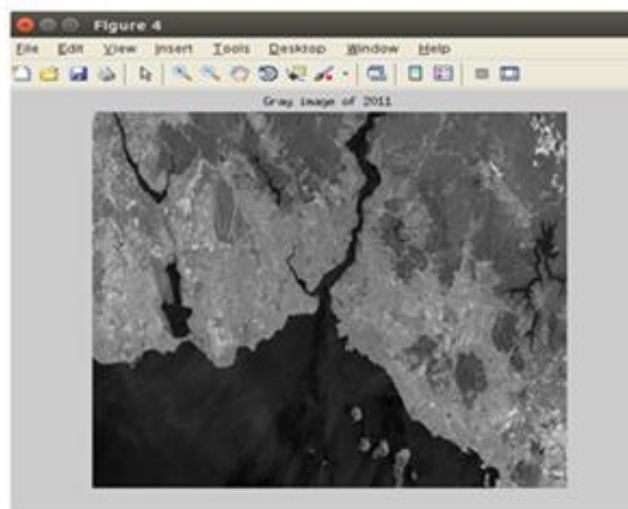


Fig. 5 Gray Scale Image of 2011

As shown in Fig. 6 it shows that, in the difference image generation step the logarithmic operator is characterized by enhancing the low intensity pixels while weakening the pixels in the areas of high intensity.

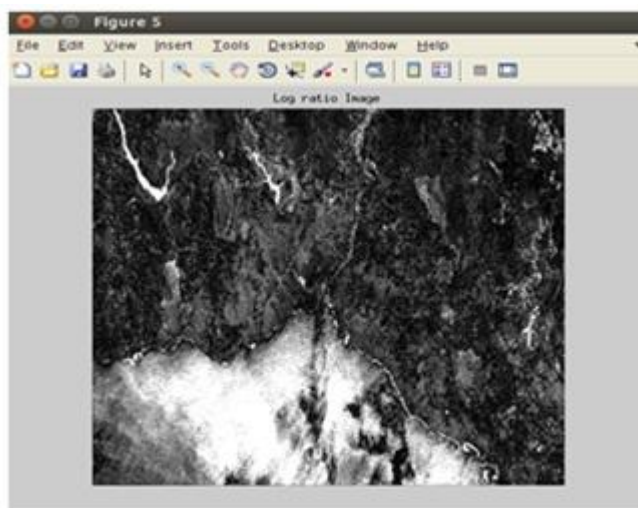


Fig. 6 Log Ratio Image

Change detection results of the SAR images shown below. Fig.7 shown below is the difference image using the Gauss-log ratio operator, the log-ratio operator, and the proposed fusion method using DWT.

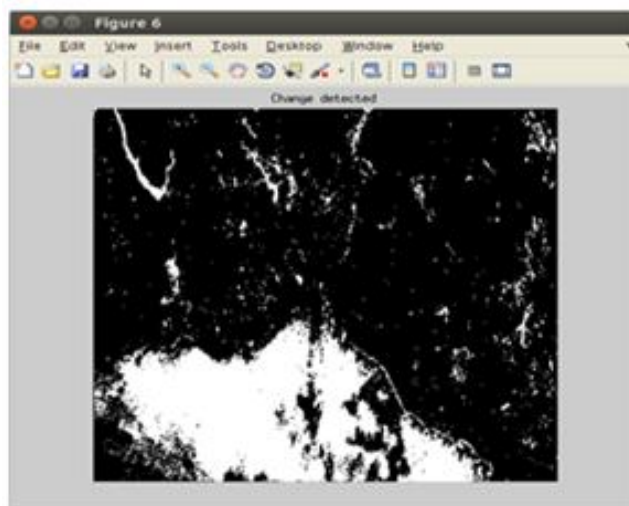


Fig. 7 Difference Image Output

As shown in the Fig.7, after generating the DI apply MRFFCM algorithm to detect changed and unchanged region in the difference image. In order to reduce the effect of speckle noise MRFFCM focus on modifying the membership instead of modifying the objective function. It is computationally simple in all the steps involved and less time consuming. Thus in the proposed system the change detection results obtained by the MRFFCM exhibits changed region more exactly than its preexistence since it is able to incorporate the local information more exactly.

## VI.CONCLUSION

In this paper, we have presented a novel unsupervised change detection approach in SAR image based on Gauss-log ratio image fusion and compressed projection. The proposed Gauss-log ratio operator can enhance the information of the changed portion in the difference image. The Gauss-log ratio image and log-ratio image are fused to produce a new difference image. NSCT is used to reduce the noise of the fused difference image and keep the object information and



edge. Compressed projection is utilized to extract feature vector for each pixel in the de-noised difference image. Finally, we use the MRFFCM algorithm to obtain the final change detection map. Simulations carried out on the widespread test real SAR images demonstrate that our approach has better performance in shape preservation compared with the existing methods. But how to classify the edge pixels more exactly is still a research direction, this issue will be possibly considered in future research.

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