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Stationary Wavelet Transform For Change Detection in Synthetic Aperture Radar Images

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Abstract
In this paper, we put forward a novel framework for change detection in synthetic aperture radar (SAR) images. The approach is based on an image fusion strategy and a novel fuzzy clustering algorithm. The significance of image fusion technique is to generate a difference image by using complementary information from a mean-ratio image and a log-ratio image. In this we are implementing Stationary Wavelet Transform (SWT) fusion technique. To restrain the background information and enhance the information of changed regions in the fused image, SWT fusion algorithm is applied on ratio images. The approach then classifies changed and unchanged regions by Markov Random Field fuzzy c-means (MRFFCM) clustering algorithm. This algorithm focuses on modifying the membership instead of modifying the objective function. Hence it is computational simple and less time consuming.

Keywords
Change detection; Synthetic aperture radar; Stationary Wavelet Transform; Markov random field; Fuzzy clustering.

I. Introduction

Image change detection means detecting the changes in images of the same scene that are taken at different times. This is of widespread interest due to a large number of applications in diverse disciplines, such as remote sensing, medical diagnosis, and video surveillance. The images generated by synthetic aperture radars (SAR) are used due to their independence of atmospheric and sunlight conditions [8]. So they have become valuable and indispensable sources of information in change detection. Generally, change detection in SAR images is the process of the analysis of two co-registered SAR images acquired over the same geographical area at different times. Such analysis is unsupervised when it aims to discriminate between unchanged and changed areas without any prior knowledge about the scene.

The procedure of change detection in SAR images can be divided into three steps [8]: 1) Image preprocessing, 2) generation of a difference image (DI) from multitemporal images, and 3) analysis of the DI. The tasks of the first step mainly include coregistration, geometric corrections, and noise reduction. In the second step, two coregistered images are compared pixel by pixel to generate the difference image. In the third step, changes are detected by applying a clustering algorithm. The performance of SAR image change detection mainly depends on the quality of the difference image and the accuracy of the classification method.

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 images. In rationing, changes are obtained by applying a pixel-by-pixel ratio operator on the 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 nonrobust to calibration errors. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale. In general, the underlying idea of the optimal difference image is that unchanged pixels exhibit small values, whereas changed areas exhibit larger values. So the optimal difference image should restrain the unchanged areas and should enhance the information of changed regions in the greatest extent. In order to solve this problem, image fusion technique based on Stationary Wavelet Transform (SWT) is introduced to generate the difference image by using complementary information from the mean-ratio image and the log-ratio image. The information of changed regions reflected by the mean-ratio image is relatively in accordance with the real changed trends in multitemporal SAR images. On the other hand, the information of background obtained by the log-ratio image is relatively flat on account of the logarithmic transformation. Hence, it can be concluded that the new difference image fused by mean-ratio image and log-ratio image provide better information content than the individual difference images.

In the difference image analysis phase, changes are usually detected by applying a decision threshold to the histogram of the difference image. Several thresholding methods have been proposed in order to determine the threshold in an unsupervised manner. SAR images are usually corrupted by speckle noise and its existence makes it difficult to seperate the two classes. Therefore, a relatively primary approach cannot perform the analysis so well. The DI-analysis step can be looked on as the process of image segmentation. We have got two conventional methods for that, the threshold method and the clustering method. In the threshold method, some essential models are usually established to search for a best threshold to divide DI into two classes. And in the clustering method, we don't need to establish a model, so it is more convenient and feasible. One of the most popular clustering methods for image segmentation is the fuzzy c-means (FCM) algorithm, which can retain more image information than hard clustering in some cases. MRF provides a basis for modeling information about the mutual influences among image pixels. An important issue of MRF is the energy function which directly characterizes the way to utilize spatial context. Considering the severe speckle noise in SAR images, determining the relationship among pixels is a complex process. Such complexity appears as two aspects: firstly, in the homogeneous region in DI, outliers disturb the utilization of the energy function, and it is not easy to stem such corruption; secondly, in the heterogeneous region in DI, an obscure boundary will emerge between two classes instead of an exact one [1]. So in order to reduce the effect of speckle noise, Markov Random Field FCM algorithm [1] is used here. This approach does not improve FCM by modifying the objective function. Instead, it focuses on the modification of the membership to reduce the effect of speckle noise. It is computationally simple, its objective function can just return to the original form of FCM

which leads to its less time consumption than some other improved FCM algorithms. It modifies the membership of each pixel by introducing the information provided by the spatial context, i.e., the neighbors of the central pixel as well as their interrelationship are concerned in the process of using MRF.
The rest of this paper is organized as follows. Section II describes the previous works. Section III describes the proposed methodology in detail. Finally, conclusion is given in Section VI.

II. Literature Survey

The performance of the proposed system mainly depends on the quality of difference image (DI) & accuracy of the classification method. Two conventional methods for difference image analysis are 1) Threshold method, 2) Clustering method. In the threshold method [3], some essential models are usually established to search for a best threshold to divide DI into two classes. Eg:-minimum-error thresholding algorithm (K&I), expectation maximization (EM) algorithm. Advantages of this approach are that it is simple and effective tool to separate objects from the background. But this approach Lack objective measures to assess the performance. Noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast etc complicate the thresholding operation. Also improper thresholding causes blotches, streaks etc on the resulting image.
But in the clustering method, we don't need to establish a model, so it seems to be more convenient and feasible. One of the most popular clustering methods for image segmentation is the fuzzy c-means (FCM) algorithm [4], which can retain more image information than hard clustering in some cases. In the standard FCM algorithm, a function that is related to the membership and dissimilarity is minimized in each iteration process, and the function is what is usually referred to as the objective function. Being able to retain more information from the original image, FCM has robust characteristics for ambiguity. However, the standard FCM algorithm is very sensitive to noise since it does not consider any information about spatial context.
Later many researchers have incorporated the local spatial and local grey level information into the original FCM algorithm to compensate this defect of FCM. In 2002 M. Ahmed, S. Yamany, N. Mohamed proposed FCM_S [5] which incorporated the local spatial and local grey level information into the original FCM algorithm. Advantages of this approach are, it was proven to be effective for image segmentation and it enhances their insensitiveness to noise. Problem with this approach is that it still lacks enough robustness to noise and outliers especially in absence of prior knowledge of the noise. In their objective functions there exists a crucial parameter α which is selected generally through experience. Also the time of segmenting an image is dependent on the image size.
Later in 2007 Chen and Zhang developed FGFCM [6] (fast generalized fuzzy c-means clustering algorithms). It incorporates the spatial information, the intensity of the local pixel neighborhood and the number of grey levels in an image. Use a new factor as a local similarity measure & remove the empirically-adjusted parameter of previous algorithm. Now the segmenting time is only dependent on the number of the gray-levels. Also this algorithm is relatively independent of the types of the noise and the value of new factor can be automatically determined. But still FGFCM has a crucial parameter 'a' which is usually obtained using trial-and-error method.
In 2010 S. Krinidis and V. Chatzis proposed FLICM [7] (fuzzy local information c-means clustering algorithm). It uses a fuzzy local similarity measure which aimed at guaranteeing noise insensitiveness and image detail preservation. Here a novel fuzzy factor G is used to improve clustering performance. It can automatically determine the spatial and gray level relationship. it improves the image segmentation performance, it is free of the empirically adjusted parameters, and also this algorithm is relatively independent of the types of noise. Balance among image details and noise is automatically achieved.
In 2012 Maoguo Gong et al proposed RFLICM (Reformulated FLICM) [8] which improved the performance of FLICM. Complementary information from the mean-ratio image and the log-ratio image is utilized to fuse a new difference image. In RFLICM It introduces a new Reformulated factor as a local similarity measure to make a tradeoff between image detail and noise. It incorporates the information about spatial context in a novel fuzzy way for the purpose of enhancing the changed information and to reduce the effect of speckle noise. This is relatively insensitive to probability statistics model. It provides accurate detection of foreground changes by fusing log ratio and mean ratio image. It is less sensitive to noises. Also FLICM is able to incorporate the local information more exactly.
In [9], authors proposed another clustering method where they used a new way for utilizing the spatial context for spatiotemporal fuzzy-control system. This SCFCM method was developed by both adding some complicated terms in the objective function and modifying the way to compute the clustering centers. In [10], the authors developed new approach by fusing Markov spatial constraint field and the fuzzy segmentation information resulting from FCM. Later in [11], FCM along with MRF was used in wavelet domain for the purpose of image segmentation.
Later they proposed MRFFCM (Markov Random Field FCM) [1]. In order to reduce the effect of speckle noise, a novel form of MRF energy function with an additional term is established to modify the membership of each pixel. And the degree of modification is determined by the relationship of the neighborhood pixels. Approach focuses on modifying the membership instead of modifying the objective function. It is computational simple in all the steps involved. Its objective function can just return to the original form of FCM, which leads to its less time consumption than that of some recently improved FCM algorithms obviously. Also this approach modifies the membership of each pixel according to a novel form of MRF energy function through which the neighbors of each pixel as well as their relationship are concerned with.
In this work we propose a new framework for change detection in SAR images. Here first we produce a difference image by applying Stationary Wavelet Transform (SWT) image fusion [2] on mean ratio and log ratio image. Then we apply MRFFCM algorithm [1] on fused difference image to classify changed and unchanged region.

III. Proposed Methodology

Image change detection is the process of identifying the changes between images of the same scene taken at different times. Change detection in SAR images is the process of the analysis of two co-registered SAR images 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 without any prior knowledge about the scene. It consists of 3 steps: 1) Image preprocessing 2) Producing difference image between the SAR images 3) Analysis

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of the difference image.

The tasks of the first step mainly include coregistration, geometric corrections, and noise reduction. Image registration is the process that transforms several images into the same coordinate system. For example, given an image and several copies of the image, with the given image as reference, Image registration can align the out-of-shape images to be the same as the given image. Thus registration is necessary in order to be able to compare or integrate the data obtained from these different measurements. Image Geometry Correction (often referred to as Image Warping) is the process of digitally manipulating image data such that the image's projection precisely matches a specific projection surface or shape. In the second step, two coregistered images are compared pixel by pixel to generate the difference image. In the DI-generation step, the logarithmic operator is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high intensity therefore, 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. The underlying idea of the optimal difference image is that unchanged pixels exhibit small values, whereas changed areas exhibit larger values. Mean-ratio shows the changed region but it doesn't enhance it. Result is better than that of log ratio operator. In order to address this problem, in this this paper we use Stationary Wavelet Transform (SWT) image fusion technique [2] to generate fused difference image by fusing log-ratio and mean-ratio image for better change detection. In the third step a Fuzzy clustering algorithm is used for classifying changed and unchanged regions in the difference image. The algorithm used is MRFFCM (Markov Random Field Fuzzy C-Means) [1]. Markov random field (MRF) serves as an opportune tool to introduce information about the mutual influences among image pixels in a powerful and formal way. MRFFCM does not improve FCM by modifying the objective function instead; it focuses on the modification of the membership to reduce the effect of speckle noise. It is of computational simplicity in all the steps involved, and its objective function can just return to the original form of FCM which leads to its less time consumption than that of some recently improved FCM algorithms obviously. It modifies the membership of each pixel by introducing the information provided by the spatial context; the neighbors of the central pixel as well as their interrelationship are concerned in the process of using MRF. Fig 1 shows the overall change detection process.

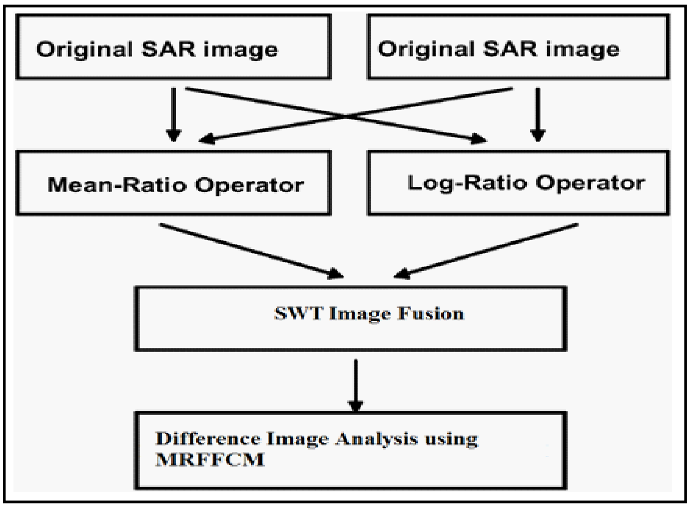

Fig. 1: Flow chart of proposed system

A. Mean-ratio and Log-ratio

The mean-ratio operator should be applied to generate the mean-ratio image. It can be defined as follows:

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

where μ_1 and μ_2 represent the local mean values of the pixels in a neighborhood of point (i,j) of multitemporal SAR images X_1 and X_2, respectively. Above equation shows that the mean-ratio operator produces difference image by using the local mean information of each pair of neighbouring pixels. The underlying idea of the optimal difference image is that unchanged pixels exhibit small values, whereas changed areas exhibit larger values. Mean-ratio shows changed region but it doesn't enhance it. Result is better than that of log ratio operator. Similarly the absolute valued log-ratio can be defined as:

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

Where, log stands for natural logarithm. The logarithmic operator is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high intensity therefore, the information of changed regions thatis 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.

B. Image Fusion using Stationary Wavelet Transform

Image fusion is the process that combines information from multiple images of the same scene inorder to extend the information content. The significance of image fusion in change detection is to produce a single difference image by combining log ratio and mean ratio images. The difference image produced by a log ratio and mean ratio alone cannot convey the real changes exactly, therefore the we produce a new difference image by fusing log ratio and mean ratio using Stationary Wavelet Transform (SWT).

The reason why we use SWT for image fusion is that compared with the other techniques SWT transforms have a better shift-invariance property and directional selectivity. It concentrates on representing point discontinuities and preserving the time and frequency details in the image. Also its simplicity and its ability to preserve image details with point discontinuities make the SWT be suitable for the change detection task. The SWT allow extracting the detail information from images by isolating frequencies in both time and space [2]. The SWT image fusion technique can be described as follows.

The two source images used for SWT fusion are obtained from the mean-ratio operator and log-ratio operator as described above. First, we compute the SWT of log-ratio and mean ratio image to obtain the multiresolution decomposition of each image. Then fuse the corresponding coefficients. Several fusion rules are used for fusing the wavelet coefficients of a low-frequency band and a high-frequency band, respectively. Finally, we apply the inverse SWT to obtain the fused image. Fig. 2 shows the overall steps of SWT image fusion process.

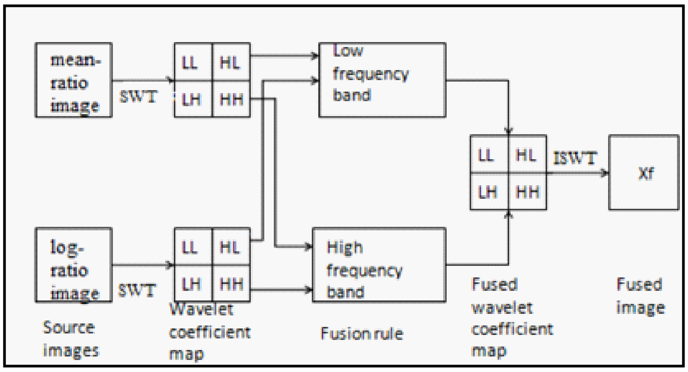

Fig.2: Image fusion based on SWT

Here X_m and X_l denotes the mean-ratio image and the log-ratio image respectively. H and L denote the high-pass and low-pass filters. LL denotes the approximate portion of the image, and LH, HL, and HH represents the horizontal, vertical, and diagonal direction portions and X_f is the fused image.

In Fig.2, we can see that first the two input images are decomposed into four sub-images of same size, where X^{LH1},X^{HL1},X^{HH1} are the high frequency subbands which corresponds to the horizontal, vertical, and diagonal direction portions. They provide information about the salient features of the source images such as edges and lines. The low-frequency subbandX^{LL1} provides information about the profile features of the input image. The fusion rule must selected such that it must be capable of restraining the background information and it must enhance the information of changed regions in a larger extend. Here two main fusion rules are used: 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:

$$D_{LL}^F = \frac{D_{LL}^m + D_{LL}^l}{2} \qquad (3)$$

$$D_\varepsilon^F(ij) = \begin{cases} D_\varepsilon^m, & E_\varepsilon^m(i,j) < E_\varepsilon^l(i,j) \\ D_\varepsilon^l, & E_\varepsilon^m(i,j) \geq E_\varepsilon^l(i,j) \end{cases} \qquad (4)$$

Here m and l represents the mean-ratio image and logratio image respectively and F denotes the new fused image.Finally ε represents HH, LH and HL which are the three high frequency bands. The energy of the coefficients can be calculated as:

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

Here E_ε (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). The wavelet coefficients of low frequency and high frequency are fused separately in the above equation.

The low-frequency sub-band reflects the profile features of the input images and thus it provides information about the changed regions of two images significantly. So in order to enhance the 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. Similarly the high frequency sub-bands reflects the salient features of the source image such as edges and lines. And it also suppresses the speckle noise. Hence, the rule of selecting the minimum local area energy coefficient is selected for merging the homogeneous regions of the high-frequency portion from the mean-ratio image and the log-ratio image. Thus we obtain the final fused difference image, now we perform classification on the difference image.

C. Main Procedure of MRFFCM

For difference image analysis Clustering Method is used. The algorithm used is MRFFCM algorithm (Markov Random Field Fuzzy C-Means) [1].The algorithm analyzes the difference image and classifies the changed and unchanged region. The main procedure of MRFFCM is as follows:

1. In the first iteration (k=1), derive the mean μi and the standard deviation σi of the two classes through the K&I method. And the initial membership matrix {uij} is generated by utilizing the original FCM algorithm unmodified (i=u, c). Then by means of hard division (the threshold of which is 0.5), generate the same-kind-number matrix $\{n_i \in \partial j\}$, and each element of the matrix denotes the number of the neighborhood pixels belonging to i.

2. In the kth iteration, establish the energy matrix $\{E_{ij}{}^k\}$.

$$E_{ij}^k = -\ln(mu_{ij}) + \beta_j(mu_{ij}, n_{ij}).t_{qj}.n_{ij} \qquad (6)$$

$$t_{qj} = sgn(u_{qj} - 0.5) \qquad (7)$$

β is an adjusting parameter and $q = x_j$

3. Using Gibbs expression, compute the pointwise prior probabilities of the MRF, and get the point wise prior probability matrix $\{\pi_{ij}^k\}$

$$\pi_{ij}^k = \frac{\exp(-E_{ij}^k)}{\exp(-E_{uj}^k) + \exp(-E_{cj}^k)} \qquad (8)$$

4. Compute the conditional probability $\{p_i^k\}$ and then generate the distance matrix $\{d_{ij}^k\}$.

$$p_i^k(y_j|\mu_i^k,\sigma_i^k) = \frac{1}{\sigma_i^k\sqrt{2\pi}}\exp\left[-\frac{(y_j-\mu_i^k)}{2(\sigma_i^k)^2}\right] \qquad (9)$$

$$d_{ij}^k = -\ln[p_i^k(y_j|\mu_i^k,\sigma_i^k)] \qquad (10)$$

5. Compute the objective function J_{ij}^k.In case of convergence exit and output $\{u_{ij}^k\}$ otherwise go to step 6

$$J_{ij}^k = \sum_{i=u}\sum_{j \in I_X}(u_{ij}^k)^2(d_{ij}^k)^2 \qquad (11)$$

$$|J_{ij}^k - J_{ij}^{k-1}| \leq \delta \qquad (12)$$

Where I_X is the DI generated by SWT fusion and $\delta$is theconvergence threshold

6. Compute the new membership matrix $\{u_{ij}^{k+1}\}$.

$$u_{ij}^{k+1} = \frac{\pi_{ij}^k\exp(-d_{ij}^k)}{\pi_{uj}^k\exp(-d_{uj}^k) + \pi_{cj}^k\exp(-d_{cj}^k)} \qquad (13)$$

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7. Update the mean and the standard deviation as μ_i^{k+1} and σ_i^{k+1}respectively. k:=k+1. Goto step 2

$$\mu_i^{k+1} = \frac{\sum_{j\in I_X}\left(u_{ij}^k y_j\right)}{\sum_{j\in I_X}\left(u_{ij}^k\right)} \tag{14}$$

$$\sigma_i^{k+1} = \sqrt{\frac{\sum_{j\in I_X}\left[u_{ij}^k\left(y_j-\mu_i^{k+1}\right)^2\right]}{\sum_{j\in I_X}\left(u_{ij}^k\right)}} \tag{15}$$

IV. Conclusions

In this paper, we have presented a novel framework for change detection in SAR-images. This approach is based on image fusion and fuzzy clustering algorithm. Our aim is to restrain the unchanged areas and to enhance the information of changed regions in the greatest extent. The information of changed regions reflected by the mean-ratio image is relative in accordance with the real changed trends in multitemporal SAR images. 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. SWT image fusion is used for that, which has better shift-invariance property and directional selectivity. Its simplicity and its ability to preserve image details with point discontinuities make the SWT suitable for the change detection task. After generating the DI we 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 SWT 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 MRFFCM exhibits changed region more exactly than its preexistence since it is able to incorporate the local information more exactly.

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