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An Efficient Approach for Change Detection in SAR 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 with a Markov Random Field (MRF). By finding the mean ratio and log ratio on the two original images the SWT based fusion rules is applied for performing image fusion. This image fusion technique is introduced to generate the difference image. Log is used to find background image and foreground detected by mean ratio. A MRFFCM 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. In order to reduce the effect of speckle noise in SAR image the MRF is established to modify the membership of each pixel. The proposed approach focuses on modifying the membership function instead of modifying the objective function to reduce the speckle noise. Its objective function returns to its original form of FCM which consumes less time than that of improved FCM algorithm. Then the approach modifies membership of each pixel according to a novel form of MRF energy function in which neighborhood pixel and their relationship are concerned. 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 the proposed approach detect the real changes as well as remove the speckle noises.

Key words: Image fusion · Clustering · Fuzzy c-means algorithm (FCM) · Synthetic Aperture Radar (SAR) · Image change detection · Markov Random Field (MRF)

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 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. 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.

An unsupervised change detection in SAR images can be divided into three steps: 1) image preprocessing; 2) producing difference image between the images; and 3) analysis of the difference image. The tasks of the first step mainly include coregistration, geometric corrections and noise reduction. In the second step, two 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 technique, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal images. And 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, instead of differencing the ratio operator is typically used operator because the image differencing technique is not adapted to the statistics of SAR images and non robust to calibration errors [1]. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale [2]. With the log-ratio operator, the multiplicative speckle noise can be

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transformed in an additive noise component. Furthermore, the range of variation of the ratio image will be compressed and there by enhances 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 ratio mean operator, the background of mean-ratio image is quite rough, for the ratio technique may emphasize the differences in the low intensities of the temporal images. In the third step, 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, such as Otsu, the Kittler and Illingworth minimum error thresholding algorithm (K&I) and the expectation maximization (EM) algorithm. 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. Various fuzzy c-means clustering algorithms were used in change detection like FCM, fast generalized FCM, FGFCM and FLICM but all those were not much efficient. FCM was very sensitive to the speckle noise.

The rest of this paper is organized as follows. Section II describes the proposed methodology in detail. Section III describes the experimental result, conclusion is given in Section IV.

Proposed Methodology: In Section III, describes the proposed change detection approach, it consist two main steps:1) generate difference image based on image fusion 2) detect the changed areas in the fused image using fuzzy clustering.

Generate the Difference Image Using Image Fusion: In image fusion, the information is obtained in greater quality by using complementary information from different source images so that the new fused images is suitable for the purpose of the computed processing tasks.

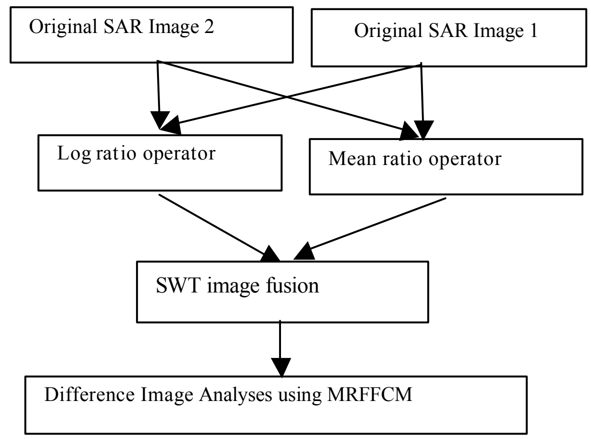

Fig. 1: Flow chart of proposed system

The image fusion techniques mainly take place at the pixel level of the source images. In particular the transforms, such as the stationary wavelet transform (SWT), contourlets, etc., have been used for the pixel level image fusion. The SWT isolates frequencies in both time and space, allow to extract the detail information from images. Compared with the other techniques SWT transforms are proved to have a better shift-invariance property and directional selectivity. The SWT 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 SWT be suitable for the change detection task. The image fusion based on the wavelet transform can be described as follows: First, the SWT of each of the two source images are computed and second to obtain the decomposition of each source image. The two source images used for fusion are obtained from the mean-ratio operator and log ratio operator as mentioned in Section II and which are commonly given by

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

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

where μ1 and μ2 represent the local mean values of multitemporal SAR images X1 and X2, respectively. In the image fusion scheme based on the wavelet transform wavelet coefficient map is obtained by taking SWT of log ratio and mean ratio images. After that fusion rules are applied. 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:

$$D_{LL}^{F} = \frac{D_{LL}^{F} + D_{LL}^{L}}{2} \tag{3}$$

$$D_{E}^{F}(\text{i,j}) = \left\{ D_{\in}^{m}(\text{i,j}) E_{\in}^{m}(\text{i,j}) D_{E}^{l}(\text{i,j}) \right. \tag{4}$$

$$D_{\in}^{l}(\text{i,j}), E_{\in}^{m}(\text{i,j}) \geq E_{\in}^{l}(\text{i,j})$$

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 coefficients. D□(i,j) represents three high-frequency coefficients at point (i,j) in the corresponding sub images. The local area energy coefficient E□(i,j) can be computed as follows:

E□(i,j)=Σk□Ni,j|D□(k)| 5)

where E□(i,j) represents the local area energy of the wavelet coefficient at point (i,j) in the corresponding sub-image and Ni,j represents the local window centred on (i,j). D□(k) denotes the value of the kth wavelet coefficient that is around the local window.

Detect Changed Areas in the Fused Image Using the Improved FCM

Fuzzy Clustering: Main objective of fuzzy c-means algorithm is to minimize:

$$J_{(U,V)} = \sum_{i=0}^{n} \sum_{j=1}^{c} (\mu_{ij})^{m} \ ||x_i - c_i||^2 \tag{6}$$

where, '$||x_i - c_j||$' is the Euclidean distance between i^{th} data and j^{th} cluster center Algorithmic Steps for Fuzzy C-means Clustering

- Randomly select *'c'* cluster centers.
- Calculate the fuzzy membership 'μ_{ij}' using:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||x_i - c_j||}{||x_i - c_i||}\right)^{\frac{2}{m-1}}} \tag{7}$$

- were $||x_i - c_j||$ is the Distance from point i to current cluster centre j, $||x_i - c_k||$ is the Distance from point i to other cluster centers k
- Compute the fuzzy centers 'c_j' using:

$$c_j = \frac{\sum_{i-1}^{N} \mu_{ij}^{m} \ x_i}{\sum_{i-1}^{N} \mu_{ij}^{m}} \tag{8}$$

- Repeat step 2) and 3) until the minimum 'J' value is achieved or $||U^{(k+1)} - U^{(k)}|| <$ â.

RFLICM Clustering: RFLICM is used to suppress the effect of speckle noise.Local coeeficient of variation is added instead of spatial distance.

$$c_u = \frac{var c_x}{(x)^2} \tag{9}$$

where var (x) and x are the intensity variance and the mean in a local window. 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.

Algorithmic Steps for RFLICM Clustering:

- Set the number of the cluster prototypes, fuzzification Parameter and the stopping conditions.
- Initialize randomly the fuzzy partition matrix u.
- Set the loop counter b=0.
- Compute the cluster prototypes using the following equation

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^{m} x_i}{\sum_{i=1}^{N} u_{ki}^{m}} \tag{10}$$

- Calculate the fuzzy partition matrix.
- If $\max\{u^{(b+1)} - u^{b}\} < \varepsilon$ then stop; otherwise, set b=b+1 and go to step (4)

Main Procedure for MRFFCM:

- In the first iteration (k = 1), derive the mean $\mu 1i$ and the standard deviation $\Sigma 1i$. In addition, the initial membership matrix $\{u1ij\}$ is generated by utilizing the original FCM algorithm unmodified ($i = u, c$).
- In the kth iteration, establish the energy matrix $\{Ekij\}$.This step is the key step to utilize the spatial context.
- Using Gibbs expression, compute the pointwise prior probabilities of the MRF and get the pointwise prior probability matrix $\{\pi kij\}$

$$\pi_{ij}^{k} = \frac{\exp - E_{ij}^{k}}{\exp(-E_{uj}^{k}) + \exp(-E_{cj}^{k})} \tag{11}$$

- Compute the conditional probability $\{p_i^k\}$ that is given by below equation generate the distance matrix

$$(y_i | \mu_i^k, \sigma_i^k) = \frac{1}{\sigma_i^k \sqrt{2\pi}} \exp\left[-\frac{(y_j - \mu_i^k)^2}{2(\sigma_i^k)^2}\right] \tag{12}$$

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

- Compute the objective function *Jkij*, shown below, where *IX* denotes the DI generated by the log-ratio operator. In case of convergence shown below, exit and output*{ {ukij}*; otherwise, go to 6. Therefore, the original FCM objective function is used

$$J_{ij}^{k} = \sum_{i=u} \sum_{j \in I_X} (\mu_{ij}^{k})^2 (d_{ij}^{k})^2 \tag{13}$$

$$J_{ij}^{k} - J_{ij}^{k-1}| \le \delta$$

- Compute the new membership that is given by, generating the new membership matrix *{uk+ij}*, which is to be used in the next iteration process

$$\mu_{uj}^{k+1} = \frac{\pi_{ij}^{k}\exp(-d_{ij}^{k})}{\pi_{uj}^{k} - \exp(d_{uj}^{k}) + \pi_{cj}^{k} - \exp(-d_{cj}^{k})} \tag{14}$$

- Update the mean and the standard deviation as *μk*+1*i* and *Σk*+1*i*, respectively, as is given shown below. *k*: =*k* + 1. Then, return to 2:

$$\mu_i^{k+1} = \frac{\sum_{j \in I_X} (\mu_{ij}^{k} y_j)}{\sum_{j \in I_X} (\mu_{ij}^{k})} \tag{15}$$

$$\sigma_i^{k+1} = \sqrt{\frac{\sum_{j \in I_X} [u_{ij}^{k} (y_i - \mu_i^{k+1})^2}{\sum_{j \in I_X} (\mu_{ij}^{k})}} \tag{16}$$

Evaluation Criteria: By presenting numerical results of a data set the performance of the proposed method is shown. That is by this quantative analysis we will prove the effectiveness of proposed change detection method.Here the dataset is of two SAR images.In this the available groundtruth image which is proposed by DWT image fusion.The experiments have been carried out for obtaining better fused image to generate Difference image. For quantitave analysis of change detection,we calculate Percentage correct classification,is given by

$$PCC = \frac{TP+TN}{N} \tag{17}$$

in common cases,the values of *PCC* by different approaches are very similar andit is difficult to observe the specific discrepancy through *PCC*. Therefore, overall error (*OE*) is applied and is defined as

$$OE = FP + FN. \tag{18}$$

KC is used to evaluate the effect of the result in the domain of image segmentation. The higher the value of *KC*, the better the segmentation result.

$$KC = \frac{PCC-PRE}{1-PRE} \tag{19}$$

In addition, the time T elapsed in the whole process is also an important criterion. It is listed to compare the time complexity of different approaches.

RESULT AND DISCUSSION

The SAR image acquired in May 1997 before flooding at Ottawa (U.S.A) is shown in Fig (2.1) is ta and the image acquired in August 1997 after flooding in Ottawa for change detection process is shown in fig (2.2). The mean ratio image shown in Fig (2.3) is obtained by mean ratio operator. It represents the local mean value of the input images. Log ratio image shown in Fig(2.4) is obtained by log ratio operator which represents the logarithmic value of the input images. SWT Fused image which generates the difference using the wavelet fusion based on mean ratio image and log ratio image is shown in Fig (2.5). MRFFCM output image in which changes are detected and speckle noises are removed is shown in Fig (2.6).

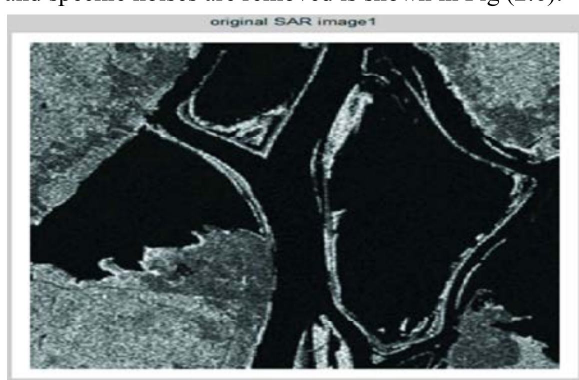

Fig. 2.1: Original SAR image 1

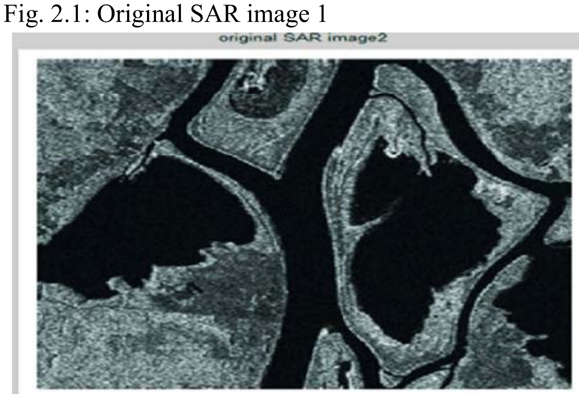

Fig. 2.2: Orignal SAR image 2

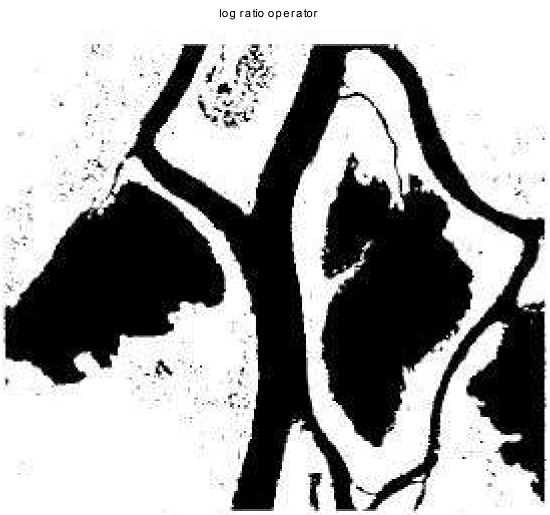

Fig. 2.3: log ratio image

Fig. 2.4: Mean ratio image

Fig. 2.5: SWT based Fused image

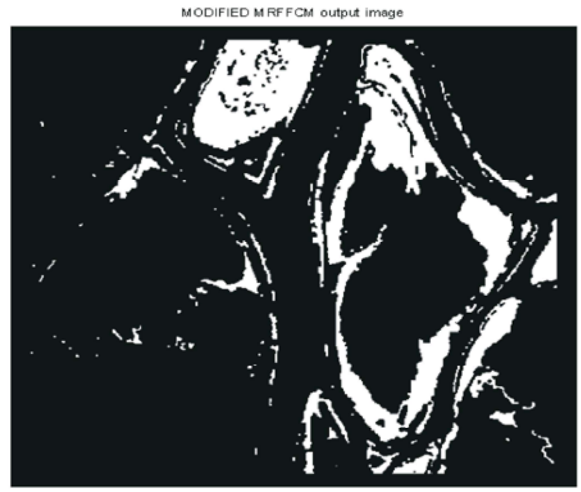

Fig. 2.6: MRFFCM output image

Table 1: Values of the evaluation criteria of the OTTAWA Dataset

Difference Image	FP	FN	OE	PCC	KC	T/s
MRFFCM	114	2248	2362	0.99	1	35.2.

CONCLUSION

In this paper, we have presented a novel approach 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. Hence, complementary information from the mean-ratio image and the log-ratio image is utilized to fuse a new difference image. SWT image fusion provides better visual quality fused image. And also the fused image can preserves more information about the edges and textures of SAR image. 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.

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