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Change Detection in SAR Images using Contourlet

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Abstract— This paper presents an unsupervised approach based on contourlet image fusion and fuzzy clustering for change detection in sar images.In this novel approach image fusion is used to produce difference image from log ratio and mean ratio images.For an optimal difference image, it should retain the unchanged areas and enhance the changed areas.so contourlet based fusion is proposed to generate the difference image. To process the difference image is to discriminate changed regions from unchanged regions using fuzzy local information c means algorithum which is insensitive to noise.Experimental result shows that this approach provides better performance than its preexistences.

Index Terms— contourlet, image fusion, fuzzy clustering, synthetic aperture radar images, change detection

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1 Introduction

CHANGE detection is a technique that identifying changes by analysing images obtained from the same geographical area at different times[1]. The changes detecting in the regions of same area at different periods is of great interest. This process have many applications in different fields .The main applications include medical diagonosis [2]-[3], remote sensing [4]-[5] [6], video surveillance [7]-[8]. One of the major data sources for remote sensing applications is synthetic aperture radar images [9]. The importance of SAR images in variety applications is because SAR sensors is adaptable to all weather conditions.The main disadvantage is presence of multiplicative speckle noise. Change detection may be done by supervised or in unsupervised manner.In supervised technique, a set of training patterns are required.it is little difficult.But in the case of unsupervised manner, there is no need of training data.so unsupervised technique is better than unsupervised techniques. [4].

In this literature, three main steps are adopted to perform unsupervised change detection,1) Preprocessing of image, 2) Comparison of image and 3)Image analysis for change detection. The main purpose of step 1 include reduction of noise,geometric and radiometric corrections and coregistration.In the second step that is after preprocessing,two sar images are taken as input and compared pixel by pixel to produce difference image.For producing difference image, ratio operator and subtraction operator are most popular techniques.In the case of rationing technique ,two preprocessed images are taken as input and applying pixel by pixel ratio operator to it,thereby changes are obtained.In the case of differencing technique , pixel by pixel subtraction is done between the 2 preprocessed images.Generally in sar images instead of differencing operator ,ratio operator is typically used.Because differencing operator is affected by caliberation errors[10].

After performing above steps change detection is done on the difference image.For this, purpose context sensitive or context insensitive methods[11] are adopted.They are of many kinds.Among them ,histogram thresholding is one method.In that method the threshold value may be detected by automatic techniques or manual trial and error mthods .There are many thresholding techniques to determine the threshold like expectation maximization algorithum[12],otsu, Kittler and Illingworth minimum-error thresholding algorithm (K&I). An optimal synthetic aperture radar image change detection is achieved by the accuracy of the classification method and quality of the difference image.In order to achieve these two qualities,we propose this change detection method.The main two steps are: 1) By fusing a mean-ratio image and a log-ratio image, difference image is produced and 2) to identify the change areas in the difference image, by using fuzzy clustering technique.This paper is composed of four sections.Section 2 involves proposed approach and our motivation will be enhanced.section 3 defines the proposed method.In section 4 includes experimental results and conclusion.

2 Motivation

Consider two mulititemporal sar images x1 and x2 as input that is taken from same geographical area at different times.The main aim is to produce difference image that consists of change information, then image analysis for change detection.According to the fig. 1 , the proposed change detection method involves mainly two steps 1) generate the difference image using contourlet fusion and 2) to identify the changed areas in fused image by fuzzy clustering.

Because of the multiplicative nature of noise, the ratio images are represented in a logarithmic [13] or a mean scale [14]. These two methods have good results for the change detection in SAR images. But it have some disadvantages.In the case of logratio image, it is not able to reflect the information

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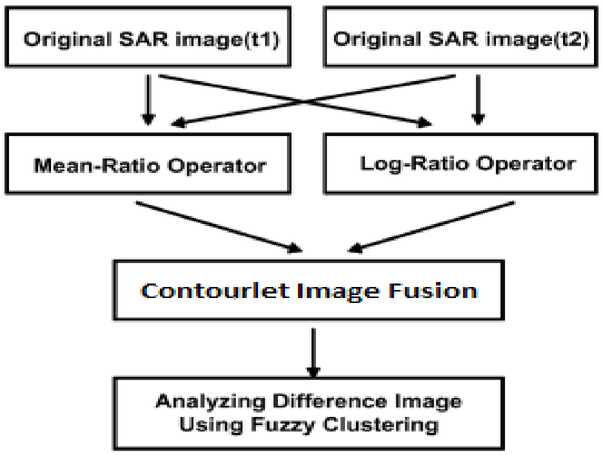

Fig.1. Block diagram of proposed change detection method

of changed regions completely. For the rmd technique, the unchanged regions of mean-ratio image are quite rough, and clarity of the image is less. For producing optimal difference image, it should restrain the unchanged areas information and should improve the information of changed regions. To solve this problem, an image fusion technique is introduced to generate the difference image.According to the literature[15],we can conclude that generating the difference image by fusing log ratio image and mean ratio image contain better information than individual difference image. Among the fusion methods pixel level image fusion is widely used [16]. Discrete wavelet transform is mostly used for pixel level image fusion.it is a multiscale transform technique..But it have lack of shift invariance property and directional selectivity.One of the important property that require for change detection is shift invariance property.The image fusion based on dwt does not preserve the fine edges and curves.And also clarity of the image is less.so we introduce image fusion by contourlet fusion.The detailed description of this method will be presented in section 3. The main purpose to analyse the difference image is to determine the changed regions and unchanged regions.Expectation maximization and K&I algorithums are mainly used to identify the changed regions.These algorithums are carried out by applying a thresholding procedure to the histogram of the image.In addition to that, these methods requires accurate estimation of threshold values.if the estimation is not correct,we cannot correctly detect the changed and unchanged regions.So in this literature,fuzzy c means clustering algorithm is proposed to analyse the difference image.it is an unsupervised technique.

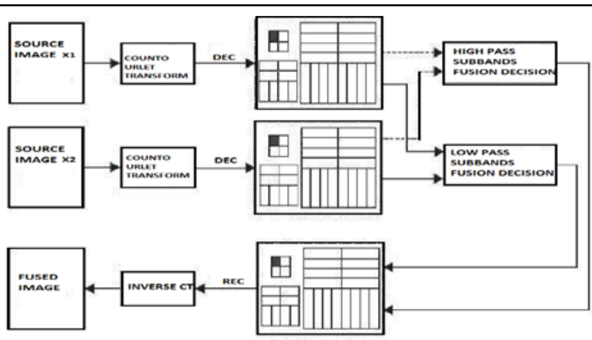

Fig. 2. Process of image fusion based on the contourlet

3 Proposed Methodology

In this section we describe the proposed change detection method,which consists of two steps; 1) Generate the difference image using contourlet fusion, and 2) Detecting changed regions using fuzzy c means clustering.

3.1 Generate the difference image based on contourlet fusion

Image fusion is a process of fusing two or more images into a single fused image, thereby relevant information in images are combined. So this single fused image will be more informative than any of the input imges [17]. The majority of fusion techniques are based on wavelet transformation. But, the DWT image fusion is resulting with shift variant and additive noise in fused image.it does not preserve edges of the image.so information loss is more.Thereby clarity of the fused image is reduced.These issues can be resolved using contourlet transform.The main properties of contourlet Transform [17] is, multiresolution, localization, directionality anisotropy and local brightness, etc. it also provide smoothness in a fused difference image .This technique is realized by double iterated filter bank.it uses laplacian pyramid and directional filter bank. There are mainly two steps for implementation of this transform.That is transformation and decomposition.

The two source images used for fusion are obtained from the mean-ratio operator and the log-ratio operator, respectively, which are given by [18].

$$Xl = [\log X2 - \log X1] \tag{1}$$

$$Xm = 1 - \min\left[\frac{m1}{m2}, \frac{m2}{m1}\right] \tag{2}$$

Where X1 and X2 are multitemporal SAR images & m1 and m2 represent local mean values of multitemporal SAR images. Fig 2 shown above represent the block diagram of the contourlet based image fusion. Here image X1 and X2 denotes the input source images respectively. F is the final fused image.The image fusion scheme based on contourlet transform can be described as follows.Mainly there are two stages, transformation stage and decomposition stage [17].

A) Transformation method

In the transformation stage, for the decomposition of subbands double filter bank is used .it is composed of laplacian pyramid and directional filter bank.so it is also called pyramidal directional filter bank. For capturing the edge point, Laplacian pyramid filter is used. Directional Filter Bank is used to link the point discontinuities in the image [19].

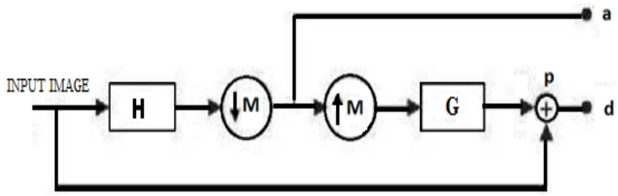

Fig. 3. Block diagram of construction of Laplacian pyramid

In this method each input image undergone subband decomposition. That is in low frequency and bandpass highfrequency subbands [19]. In the case of low frequency subband, the same process is repeated upto specified contourlet decomposition level. Above block diagram fig. 3 shows the laplacian pyramid decomposition.Here the input image is fed to a low pass analysis filter (H) and then down sampled to lowpass Subband. Then this image is up sampled and applied to a synthesis filter (G). Finally subtracting the output of the synthesis filter and input image we get highpass subbands [17]. The laplacian pyramid also allows high frequency bandpass image s into further decomposition.That is this bandpass images are passed through the directional filterbank. It captures directional information accurately.So in this tranfomation stage, it decomposes the image into directional subbands at multiscale.

B. Decomposition Method

In this stage, decomposed subbands of transformation stage are fused by fusion rules.There are separate fusion rules for lowpass and highpass band. The coefficients in the lowpass subband a represents the profile features of the source image. For this measurement local area energy contourlet domain is used. Then the selection and averaging modes are used to compute the final coefficients [19].

The local energy E(x,y) is calculated by [17]

$$E(x,y)=\sum_m \sum_n a_j(x+m,y+n)^2 W_L(m,n) \qquad (3)$$

Where (x,y) denotes the current contourlet coefficient, WL(m,n) is a template of size 3*3 [17]. High frequency subbands which represent the salient features of the source image such as curves and lines.Average method is used for fusing the highfequency subbands. It is defined as follows; [18].

$$E^F{}_{j,k}(x,y) = d^A{}_{j,k}(x,y) + d^B{}_{j,k}(x,y) \qquad (4)$$

Where $E^F{}_{j,k}(x,y)$ is the local energy, $d^X{}_{j,k}(x,y)$ is the high frequency coefficent.Finally fused image is obtained from inverse contourlet decomposition method. The proposed method can provide fused image with better visual quality. And also the resultant fused image can preserve much information of edges and textures of SAR image.In the next section we describe novel fuzzy clustering algorithm for change detection in contourlet fused image.

3.2 Analysis of fused image using fuzzy clustering

Clustering means partioning a data set into a reasonable number of disjoint groups where each group containing similar samples[20].In this partitions ,patterns are similar within the clusters and different between the clusters.In fuzzy clustering the samples are assigned not only to one cluster In fuzzy clustering the samples are assigned not only to one cluster,but belongs to different clusters.That is samples with certain degree of belonging to all clusters.Among the fuzzy clustering methods, the FCM algorithm [21] is one of the most popular methods since it can retain more information from the original image and has robust characteristics for ambiguitys.Here clustering is done to discriminate changed regions from unchanged regions. For improving the performance of image clustering, we use improved version of fuzzy clustering technique.That is fuzzy local information c means clustering algorithum. Here we introduce, a novel fuzzy factor into the object function of FLICM.The peculiarity of fuzzy local information c means algorithum is the main use of local similarity measure,which is aimed at ensuring the image detail preservation and noise insensitiveness.This fuzzy factor is [18],

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d_{ij}+1}(1-u_{kj})^m \|x_j - v_k\|^2 \qquad (5)$$

Where dij is the spatial Euclidean distance between pixels i and j. i th pixel represents the center of the local window and jth pixel is the neighboring pixels falling into the window around the ith pixel.vk represents the prototype of the center of cluster, and ukj represents the fuzzy membership membership of the gray value j with respect to the kth cluster. Some of the properties of new fuzzy factor includes: Preserving image details without setting an artificial parameter, incorporate local gray and spatial level information in order to preserve robustness and noise insensitiveness. The objective function of the FLICM is described as follows [18] [22]

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}}\right)^{1/(m-1)}} \qquad (6)$$

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c}\left[u_{ki}^m \|x_i - v_k\|^2 + G_{ki}\right]$$

$$\nu_k = \frac{\sum_{i=1}^{N} u_{ki}^m x_i}{\sum_{i=1}^{N} u_{ki}^m} \qquad (8)$$

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FLICM algorithm [18] [22] is described as follows:
Step1) Initialize the number of the cluster prototypes, fuzzification parameter *m* and the stopping condition ε.
Step 2) Initialize randomly the fuzzy partition matrix.
Step 3) Then set the loop counter b=0.
Step 4) Compute the cluster prototypes.
Step 5) Also Calculate the fuzzy partition matrix.
Step 6) max *{U (b) - U (b+ 1)}* < *ε* then stop; otherwise, set b=b+1, and go to step 4.

4 Experimental Study

By presenting numerical results on five data sets we will show the performance of the proposed method. That is by this quantative analysis we will prove the effectiveness of proposed change detection method.Here only images of two dataset is shown. In this analysis ,the first data set contain a ection of two SAR images of Dubai obtained in the years of 2000 and 2010 respectively shown in Fig. 4(a) and 4(b). The available ground truth (reference image) is shown in Fig. 4(d). The Fig. 4(c) Shows the proposed contourlet fused image. The second data set is a section of two SAR images over the area of Istanbul. That is multitemporal images relating to Istanbul used in the experiments. In fig 5(a) Image acquired in 1975 and 5 (b) Image acquired in 2011. In fig 5(c) fused image is shown. The available ground truth is shown in Fig. 5(d). The experiments have been carried out for obtaining better fused image. That is here analyzing the effectiveness of the contourlet fusion strategy to generate the difference image. And, we compared the change detection performance of our algorithm with other two methods, including the DWT and the mean ratio operation. We presented a comparative analysis for the suitability of the proposed approach for the fused difference image. .For quantative analysis of change detection, we calculate the Percentage Correct Classification [23] which is given by [18].

TABLE 1
Change Detection Results Based on DWT Fusion

DWT Fusion	
Image Set	Image Fusion Results (PCC)
Dubai	91.56
istanbul	87.87
tehran	80.46
washington	82.07
lasevegas	63.68

$$PCC= (TP+ TN)/ (TP+ FP+ TN+ FN)$$

Here, TP is the number of pixels that are detected as the changed area .TN is the number of pixels that are detected as the unchanged area. The false negatives (FN) are the changed pixels that an undetected.False positive (FP) is the unchanged pixels wrongly classified as changed. In this experiment, we analyzed the effectiveness of contourlet image fusion technique to generate the difference image. As shown in Table I, the change detection results of the fused difference image were compared with the ones generate from mean-ratio operator and dwt by Istanbul and dubai.And the proposed fusion method resulted in highest PCC value than other methods.

TABLE 2
Change Detection Results Based on Contourlet Fusion

Contourlet Fusion	
Image Set	Image Fusion Results (PCC)
Dubai	94.05
istanbul	89.83
Tehran	82.07
washington	83.71
lasevegas	63.96


Fig. 4a. Duabi in 2000


Fig. 4b. Dubai in 2010

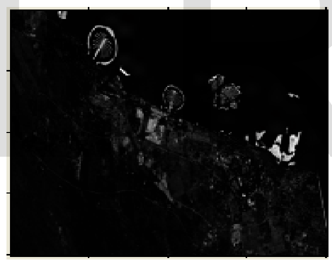
Fig. 4c. Fused Image


Fig.4d Change detected Image

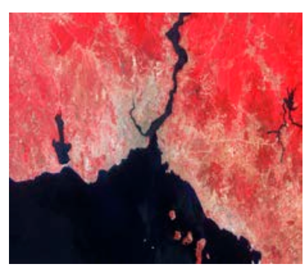
Fig. 5a. Istanbul in 1975

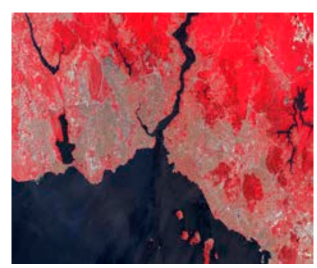
Fig. 5b. Istanbul in 2011

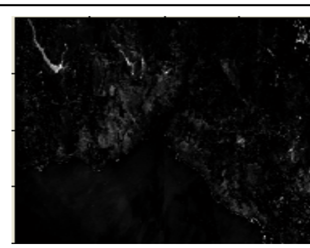
Fig. 5c. Fused image

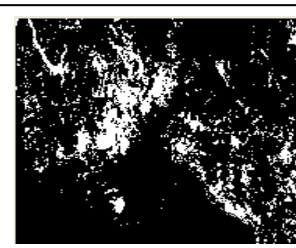
Fig. 5d. Change detected image

5 Conclusion

In this paper, we have presented an unsupervised approach based on contourlet fusion and fuzzy clustering for change detection in sar images.In order to restrain the unchanged areas and enhance the changed areas, fusion approach is used.Among the fusion methods, the limitations of wavelet transforms is capturing the geometry of image edges. so in this paper, we pursue contourlet transform that can capture the intrinsic geometrical structure that is key in visual information. .We will show that, this method can provide fused image with better visual quality. In addition to that difference image produced in this method is better than that of dwt fused difference image. The obtained fusion image can preserve much information of edges and textures of SAR images. The experiment results also show that the proposed contourlet 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 FLICM are better than the pre-existence.

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