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Change Detection in Satellite Images Using Contourlet Transform and RFLICM Clustering

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Abstract *-An approach based on contourlet image fusion and reformulated fuzzy clustering for change detection in satellite images is introduced in this paper. In this approach fusion of images is used to produce difference image from log ratio and mean ratio images. An optimal difference image should retain the unchanged areas and show the changed areas. So contourlet image fusion is used to generate the difference image. Processing the difference image means to discriminate changed regions from unchanged regions using reformulated fuzzy local information c means algorithm. It is used because it is very sensitive to noise. Experimental result shows that this approach provides better performance than the previous methods.*

Key words– contourlet, image fusion, reformulated fuzzy clustering, satellite images, change detection.

1. INTRODUCTION

Change detection is a technique to identify changes occured by analyzing images obtained from the same geographical area captured at different times [1]. Detecting changes occurred in the regions of same area at different times is of great interest. The main applications of this process include medical diagnosis [2]-[3], remote sensing [4]-[5] [6], video surveillance [7]-[8].Process of change detection can be done using supervised or in unsupervised manner.In supervised technique, a set of training data are required which is very difficult.But in the case of latter, there is no need of training data. To reduce the complexity unsupervised technique used [4].In this paper, three main steps are there to perform unsupervised change detection,1) Preprocessing of image, 2) Comparison of image and 3) Image analysis. The main aim of step 1 includes noise reduction,geometric corrections and co-registration.In the next step,to produce difference image, two satellite images are taken and compared pixel by pixel.Subtraction operator and ratio operator are the common methods to produce difference image. In the case of ratio operator, two preprocessed images are taken as input and applying pixel by pixel ratio operator to it,thereby changes are obtained. In differencing method, pixel by pixel subtraction is done between the two images.Because differencing operator is affected by calibration errors[9] in satellite images ratio operator is used.

After obtaining the difference image change detection technique is applied.For this, context sensitive or context insensitive methods[10] are used.They are of many types of this methods.Among them, histogram thresholding is one method in which the threshold value is detected by automatic techniques or trial and error methods .To obtain the threshold there are many techniques like expectation maximization algorithm[11],otsu, Kittler and Illingworth minimum-error thresholding algorithm (K&I). Optimal satellite image change detection mainly focus on the accuracy of the clustering method and quality of the fused image.To achieve these two targets,we propose this change detection method consist of mainly two steps: 1) By fusing a mean-ratio image and a log-ratio image, fused image is produced and 2) to identify the changed areas in the fused image, by using reformulated fuzzy clustering technique.This paper is composed of four sections.Section 2 involves our motivation to do this. Section 3 defines the proposed method.In section 4 includes experimental results and conclusion.

2MOTIVATION

The input images are taken from same geographical area at different times.The main aim is to produce fused image that enhance the changedinformation, then analysis of image is performed for change detection.Fig: 1 shows the flowchart of our proposed method. It shows the main two steps in this method 1) generate the difference image using contourlet fusion and 2) to identify the changed areas in fused image byreformulated fuzzy clustering.

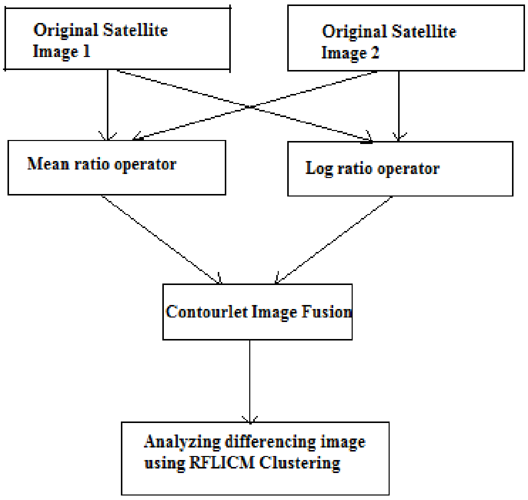

Fig: 1 Flowchart of proposed change detection approach

Because of the presence of noise[11] in satellite images, the ratio images are first converted to logarithmic [12] or a mean scale [13],because when representing the image as log ratio operator the multiplicative noise is converted to additive noise. It enhances the low intensity pixels. Thereby the unchanged regions are clearer from this image. But this scale weakens the pixels in the high intensity regions. So the changed regions cannot be clearly distinguished. To get the whole changed regions rmd method is used. In rmd the changes in the image is appeared as the local mean value of image. This enhances the high intensity pixels thereby the changed regions. The main idea of the difference image is that to discriminate the image such that the unchanged area has small value and changed area has large value. To obtain this image fusion method is used.In this method the log ratio image and mean ratio images are compared or fused using certain fusion rules and can obtain an image which enhances the changed regions without any change in the background image. Among the fusion methods pixelwise image fusion is used [14]. Discrete wavelet transform is commonly used for pixel level image fusion. It is a multiscale transform technique. But it doesn't have directional selectivity.The image fusion based on dwt does not preserve the fine edges. and curves.And also clarity of the image is less. So contourlet fusion is used.The detailed description of this method will be presented in section 3. Next process is to analyze the fused image. The analysis includes the classification of changed and unchanged area.The common method for classification is EM algorithm and K&I algorithm both are using a thresholding procedureto the histogram of image. The calculation of threshold is much difficult and the output will not much accurate. To increase the quality FCM is used. This method also reduces the noise.

3 PROPOSED METHODOLOGY

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

3.1Generate the fused image using on contourlet fusion

Image fusion is a process in which the important information in images is combined. So the single fused image will be more informative than any of the input images [15]. Wavelet transformation is the commonly used fusion technique. 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 quality of the fused image is reduced. These issues can be resolved using contourlet transform. The main properties of contourlet Transform [16] is, multiresolution, localization, directionality anisotropy and local brightness, etc. It also provides greater quality in a fused difference image. This technique uses double iterated filter bank. They are 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 [17]

$$X_l = [\log(X2)-\log(X1)]$$

$$X_m = 1-\min\left(\frac{m1}{m2}, \frac{m2}{m1}\right)$$

Where X1 and X2 are satellite images & m1 and m2 represent local mean values of satellite images. The image fusion scheme based on contourlet transform can be described as follows.Mainly there are two stages, transformation stage and decomposition stage [15].

A) Transformation method

In the transformation stage, double filter bank is used for the decomposition of subbands. Double filter bank consist of laplacian pyramid and directional filter bank.Laplacian pyramid filter is used for capturing the edge point, Directional Filter Bank is used to provide continuity in the image [18].

In this method each input image undergo subband decomposition in low frequency and bandpass high frequency subbands [18]. Block diagram fig. 2 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.

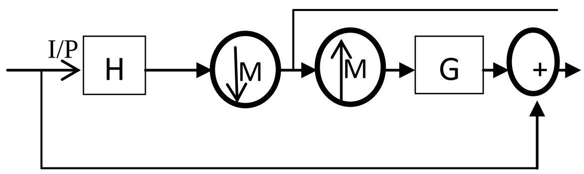

Fig: 2 Block diagram of construction of laplacian pyramid

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 [16]. This output image is fed to further decomposition. That is this images are passed through the directional filterbank which captures directional information correctly. So in this transformation stage, it decomposes the image into directional subbands.

B) Decomposition Method

In this stage, decomposed subbands of transformation stage are fused by fusion rules. Lowpass and highpass bands are fused separately using separate fusion rules. The profile features of the source image are represented by coefficients of lowpass subband. For this measurement average method is used.High frequency subbands which represent the salient features of the source image such as curves and lines and for this measurement mean value coefficient is used.

$$C^{ll} = \frac{C1+C2}{2}$$

$$C^{hh} = \begin{cases} C1 & \text{if } mean(C1^2)>mean(C2^2) \\ C2 & \text{if } mean(C2^2)>mean(C1^2) \end{cases}$$

where c^{ll} and c^{hh} are low frequency and high frequency coefficients respectively and c1 and c2 are decomposed images. Using inverse contourlet decomposition method the original image can be reconstructed. 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 satellite image. In the next section we describe reformulated fuzzy clustering algorithm for change detection in contourlet fused image.

3.2 Analysis of fused image using reformulated fuzzy clustering

Clustering means classifying a data set into two disjoint groups in which each group containing similar samples[19].In this clustering, samples are similar within the cluster and different between the clusters. Among the fuzzy clustering methods, the FCM algorithm [20] is one of the most popular method.It can conserve more information from the original image. Another improved version of fuzzy clustering technique is introduced to improve the performance of clustering. That is fuzzy local information c means clustering algorithm[21]. A fuzzy factor is introduced as objective function of this algorithm. To ensure the image data preservation and to make it insensitive to noise we use a local similarity measure, which is the peculiarity of FLICM. In the analysis of fuzzy factor the local gray level information and spatial information in it are represented by the gray level difference and spatial distance and the local spatial relationship changes according to spatial distances from the central pixel. In FLICM damping extent of the neighbors with the spatial distances from the central pixel is calculated. The spatial distance used to measure the damping extent of the neighbors may be corrupted by noise in some cases. For example,

Case 1) the central pixel is not noise. Some pixels of neighboring pixels within the local window may be corrupted by noise. In fig 3(a) a 3×3 window that is taken from the noisy image, and Fig. 3(c) showsits damping extent of the neighbors with the spatial distances. For the noisy pixels of A and B, the gray-level difference between pixel A and the central pixel is greater than pixel B. To suppress the influence of the noisy pixels, the weightings added of pixel A in fuzzy factor should be greater than the noisy pixel B. However, from the damping extent of the neighbors with the spatial distances we cannot determine which is the noisy pixel [Fig. 3(c)].

A120	22	13
32	20	35
28	B90	27

(a)

87	99	116
90	20	67
110	88	75

(b)

0.414	0.5	0.414
0.5		0.5
0.414	**0.5**	0.414

(c)

Fig: 3A 3×3 window with noise and their damping extent of the neighboring pixels. (a) Central pixel is not noise. (b) Central pixel is corrupted by noise. (c)Damping extent of the neighboring pixels.

Case 2) The central pixel is corrupted by noise. The other pixels within its local window are not corrupted by noise. Fig 3(b) shows this. In this case, the gray-level differences between the neighboring pixels and the central pixel are almost different. The damping extent of the neighbors that is calculated is simply divided into two categories (0.414 and 0.5). It fails to analyze the impact of each neighboring pixel onto the fuzzy factor.

The above cases show the importance of calculating the correct fuzzy factor to suppress the influence of noisy pixels. For the effective calculation of fuzzy factor, the local coefficient of variation is introduced to replace spatial distance to reduce the effect of noise.The local coefficient of variation $C_u$is given by,

$$C_u = \frac{var(x)}{(\bar{x})^2}$$

where var(x) and $\bar{x}$ are the intensity variance and the mean of a local window of the image.The value of C_u shows the gray-value homogeneity degree of the local window. It has high values at edges or in the area corrupted by noise and low values in other regions. The damping extent of the neighbors with local coefficient of variation is measured by the neighbor pixels located. If the neighbor pixel and the central pixel are located in the same region, or the area corrupted by noise, the results of the local coefficient of variation will be very close and vice versa. In general, compared with the spatial distance, the local coefficient of variation between neighboring pixels and the central pixel is dependent to the gray-level difference between them. The modified fuzzy factor can be defined as

$$G'_{ki} = \begin{cases} \sum_{j \in N_i} \frac{1}{2+\min\left((C_u^j/C_u)^2,(C_u/C_u^j)^2\right)} \\ \quad \times (1-u_{kj})^m \|x_j - v_k\|^2, & \text{if } C_u^j \geq \overline{C_u} \\ \sum_{j \in N_i} \frac{1}{2-\min\left((C_u^j/C_u)^2,(C_u/C_u^j)^2\right)} \\ \quad \times (1-u_{kj})^m \|x_j - v_k\|^2, & \text{if } C_u^j < \overline{C_u} \end{cases}$$

where C_u is the local coefficient of variation of the central pixel, C_u^j represents the local coefficient of variation of neighboringpixels, and $\overline{Cu}$ is the mean value of C_u^j that is located in a localwindow.

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

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

vk represents the center of cluster,and ukj represents the fuzzy partition matrix. The reformulated factor balances the membership value of the central pixel, the local coefficient of variation, as well as the gray level of the neighboring pixels. If there is a distinct difference between the results of the local coefficient of variation that are obtained by the neighboring pixel and the central pixel, the weightings added of the neighboring pixel in fuzzy factor will be increased to suppress the influence of noise; thereby, RFLICM, is expected to be more robust to its preexistence. RFLICM algorithm can be described as follows:

Step1) Initialize the number of the cluster prototypes, fuzzificationparameter 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 center.
Step 5) Also Calculate the fuzzy partition matrix.
Step6) 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 quantitative analysis we will prove the effectiveness of proposed change detection method. Here only images of two dataset are shown. In this analysis ,the first data set contain a section of two satellite images of Washington obtained in the years of 1984 and 2011 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 satellite images over the area of China. In fig 5(a) Image acquired in 1973 and 5 (b) Image acquired in 2003. 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 to generate the difference image and the effectiveness of reformulated fuzzy clustering algorithm. And, we compared the change detection performance of our algorithm with other method, using the DWT and the FLICM clustering. We presented a comparative analysis for the suitability of the proposed approach for the fused difference image and clustering.For quantitative analysis of change detection, we calculate the Percentage Correct Classification [23] which is given by [18].

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 are 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 and RFLICM technique to cluster the image. As shown in Table I, the change detection results of the fused difference image and clustered image were compared with the ones generate from FLICM clustering and dwt by Washington and China. And the proposed method resulted in highest PCC value than other method.

Table 1
Change Detection Results Based on DWT Fusion and FLICM Clustering

Table 2
Change Detection Results Based on Contourlet Transform and RFLICM Clustering

DWT fusion and FLICM clustering	
Image set	PCC
Washington	85.33
China	65.34
Chicago	74.26
Tokyo	87.76
Vegas	56.47

Contourlet Fusion and RFLICM clustering	
Image set	PCC
Washington	86.96
China	76.86
Chicago	77.11
Tokyo	90.27
Vegas	57.07

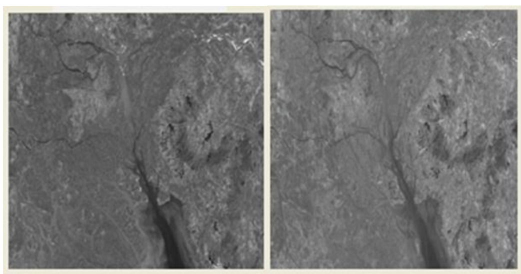

Fig:4a China in 1973 Fig:4b China in 2003

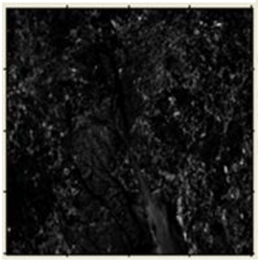
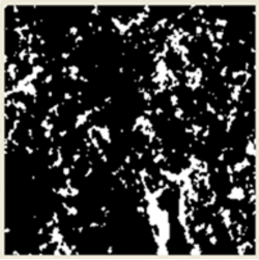

Fig:4c Fused image Fig:4d Change detected image

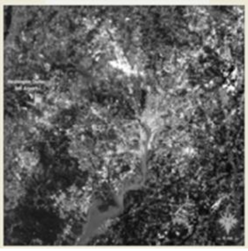
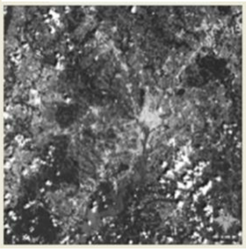

Fig: 5a Washington in 1984 Fig: 5b Washington in 2011

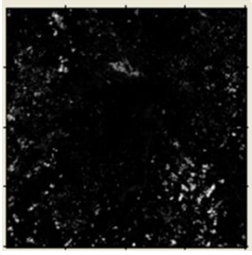


Fig: 5c Fused image Fig:5d Change detected image

5CONCLUSION

In this paper, we have presented an approach based on contourlet fusion and reformulated fuzzy clustering for change detection in satellite images.Among the fusion methods, the limitations of wavelet transforms are capturing the geometry of image edges. So in this paper, we propose contourlet transform that can capture the intrinsic geometrical structure that is key in visual information. 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 satellite 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 RFLICM algorithm that incorporates both local spatial and gray information is proposed, which is relatively insensitive to probability statistics model. The RFLICM algorithm introduces the reformulated factor as a local similarity measure to make a tradeoff between image detail and noise. Compared with the original algorithms, RFLICM is able to incorporate the local information more exactly.The change detection results obtained by the RFLICM exhibited less spots than its preexistence (i.e., FLICM) since it is able to incorporate the local information more exactly.

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