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CHANGE DETECTION IN OPTICAL IMAGES USING DWT IMAGE FUSION TECHNIQUE AND FUZZY CLUSTERING

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Abstract

This paper presents a change detection approach for optical image based on an DWT image fusion technique and fuzzy clustering algorithm. In this paper we first perform the mean ratio operator and log ratio operator onto the two original optical images and apply the DWT based fusion rules for performing image fusion and then apply the FLICM fuzzy clustering technique for DWT based fused image. The DWT image fusion technique is to produce a difference image by using complementary information from a mean ratio image and a log ratio image. A fuzzy local-information C-means (FLICM) clustering algorithm is proposed for classifying changed and unchanged area in the fused difference image. The FLICM clustering algorithm incorporates the information about spatial context in a fuzzy way for the purpose of enhancing the changed information and reducing the effect of noise. By using FLICM clustering algorithm we get better performance and lower error than the pre-existence.

Keywords*:* Change detection, clustering, fuzzy c-means (FCM) clustering algorithm, fuzzy local information c-means (FLICM) clustering algorithm, Image Fusion and Discrete wavelet transform (DWT).

1. Introduction

Image change detection is process that analyzes images of the same scene taken at different times in order to identify the changes that may have occurred between the acquisition dates [1]-[6]. The different application for the change detection such as remote sensing, medical diagnosis, video surveillances and civil infrastructure. Among all these applications change detection in synthetic aperture radar (SAR) images having more difficulties than the optical one because the SAR images suffer from the presence of the speckle noise [7]-[10]. Working with microwave SAR can acquire images under any atmospheric condition and independently of solar illumination [11]. Change detection techniques developed in various application domains for the comparative analysis of very high resolution images result ineffective when applied to the remote sensing images.

In the literature, usually change detection in optical image is based on three step procedure: 1) Image preprocessing; 2) Generate the difference image between the multitemporal images; and 3) Analysis of the difference image. In the first step the purpose of the image preprocessing is to reduce the noise. In the second step, two pre-processed images are compared pixel-by-pixel to produce the difference image. Generally, there are differencing (Subtraction operator) and rationing (ratio operator) are well-known techniques to generates the difference image. In differencing, subtracting intensity values pixel-by-pixel between the considered couple of temporal images. In rationing, apply the pixel-by-pixel ratio operator to the considered couple of temporal images. Last step, by applying the DWT Image fusion technique and FLICM clustering algorithm of the difference image.

In general, overall performance of change detection in optical image depends on quality of the difference image and accuracy of the classification method. There are generally, two issues; 1) Generate the difference image by fusing a mean-ratio image and log-ratio image, and 2) By applying the fuzzy local-information C-means (FLICM) clustering algorithm to the difference image which is insensitive to noise since to identify the changed regions in the difference image.

This paper is divided into five sections. Section-II describes the literature survey. Section-III describes the proposed method in details. Section-IV presents the experimental result on real multitemporal Optical images will be described to demonstrate the effectiveness of the proposed approach. The last section presents the conclusion.

2. Literature Survey

Detecting regions of change in multiple images of the same scene taken at different times is of widespread interest due to a large number of applications in diverse disciplines, including remote sensing, surveillance, medical diagnosis and treatment, civil infrastructure, and underwater sensing. A systematic survey of the common processing steps and core decision rules in modern change detection algorithms, including significance and hypothesis testing, predictive models, the shading model, and background modelling. We also discuss important pre-processing methods, approaches to enforcing the consistency if the change mask, and principles for evaluating and comparing the performance of change detection algorithms [8].

The proposed approach exploits a wavelet-based multiscale decomposition of the log-ratio image (obtained by a comparison of the original multitemporal data) aimed at achieving different scales (levels) of representation of the change signal. Each scale is characterized by a different trade-off between speckle reduction and preservation of geometrical details. For each pixel, a subset of reliable scales is identified on the basis of a local statistic measure applied to scale-dependent log-ratio images. The final change detection result is obtained according to an adaptive scale-driven fusion algorithm [9].

3. Methodology

In this section, we focus on describing the proposed change detection approach, which is having the two main steps: 1) Generate the difference image based on DWT image fusion Technique and 2) Detect the changed area in the fused image using FLICM algorithm.

1) Generate the difference image based on DWT image fusion Technique

The ratio difference image is usually expressed in a logarithmic or a mean scale due to presence of the noise. The two images from the mean-ratio operation and log-ratio operation are fused to get the difference image. The difference image modifies the background information as well as the changed information [12]. Thus the image fusion introduced the effect of log-ratio and mean ratio operator and we can introduce the difference image.

The DWT image fusion technique is introduced to generate the difference image by using complementary information from several source images. DWT Image fusion techniques mainly take places at the pixel level of the source (original) image [13]-[15]. In particular multiscale transforms such as discrete wavelet transform (DWT), curve lets, contour lets etc.., have been used for pixel level image fusion. The DWT isolates frequencies in both time and space allowing detail information extracted from images. Compared with the DWT transform

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technique are proved to have a better shift-invariance property and directional selectivity. The DWT concentrates on representing point discontinues and preserving the time and frequency details in the image.

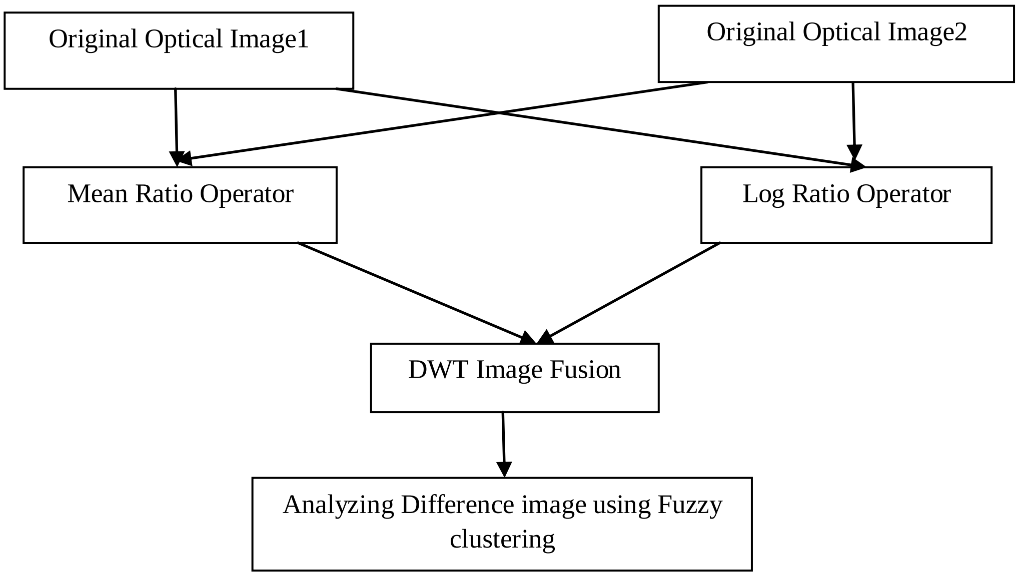

Figure 1. Proposed approach for Change Detection

The two source images used for image fusion are obtained from the mean-ratio operator and log-ratio operator which are commonly given by,

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

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

Where µ1 and µ2 denotes the local mean values of multitemporal images X1 and X2 respectively.

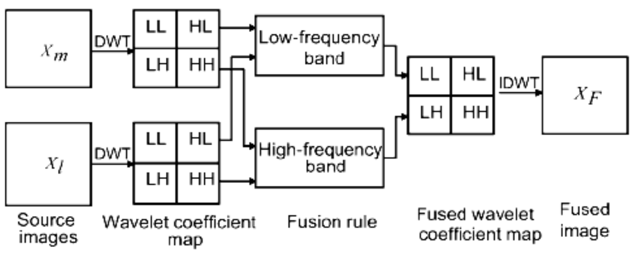

Figure 2. Process of image fusion based on the DWT

The discrete wavelet transform can be described as: First we calculate the DWT of each of the two source images and obtain the multiresolution decomposition of each source image [16]. Then we fuse respective coefficients of the frequency. The wavelet coefficients are fused by using different fusion rule such as high-frequency band and low-frequency band. Finally, the inverse DWT is applied to the fused wavelet coefficients [17].

In the above fig. Xm and Xl represents the mean-ratio image and the log-ratio image respectively. H and L represent the high-pass and low-pass filters respectively. LL represents the approximate portion of the image and LH, HL and HH represents the horizontal, vertical and diagonal direction portions. The main goal of the fusion rule is to modify the magnitude of the coefficients of the fused image [2].

The decomposition level can be obtained from low-level frequency bands and high-level frequency bands. It is necessary to fuse the wavelet coefficients using various different fusion rules for the bands. The main purpose of the proposed method to generate difference image is the selection of fusion rules, which should restrain the unchanged area information and to modify the information of changed area. The main purpose of these fusion rules is to modify the magnitude of the coefficient of the fused image [18].

The two main fusion rules are as follows: i) The rule of selecting the average value of corresponding coefficients for the low-level frequency band. ii) The rule of selecting the minimum local area energy coefficients for the high-level frequency band.

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

$$D_{\varepsilon}^{F}(i,j) = \{\, D_{\varepsilon}^{m}(i,j),\ E_{\varepsilon}^{m}(i,j) < E_{\varepsilon}^{l}(i,j) \qquad (4)$$

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

Where *m* and *l* represent the mean-ratio image and the log-ratio image, respectively. F denotes the new fused image. D_{LL} stands for low-frequency coefficients. D_{ε} (i,j) ($\varepsilon = LH, HL, HH$) represents three high-frequency coefficients at point in the corresponding sub images. The local area energy coefficients $E_{\in}(i,j)$ can be calculated are as follows:

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

Where $E_{\in}(i,j)$ represents the local area energy coefficients at point (i,j) in the corresponding sub images and $N_{i,j}$ represents the local window centered on (i,j), $D_{\in}(k)$ denotes the value of the k^{th} coefficients.

In (3) and (4) the wavelet coefficients of low-level frequency and high-level frequency are fused separately. The low-level frequency sub-band, which represents the profile features of the source (original) image and significantly reflects the information of changed regions of two source (original) images. Hence, in order to modify the gradient or edge features of the changed regions, the rule of the average operator is selected to fuse the wavelet coefficients for the low-level frequency sub-band. In the other hand, the high-level frequency sub-band, which indicate the information about the salient features of the source (original) images such as edges and lines and it also suppresses the noise. This rule is used to merge the homogeneous regions of the high-level frequency portion from the mean-ratio image and the log-ratio image.

2) Detect the changed area in the fused image using FLICM algorithm

The main purpose to process the difference image is to discriminate changed area from unchanged area. In addition, the clustering algorithm is unrestricted by the statistical model for change and unchanged region distributions, which provides it broad prospects in Optical image change detection.

Among the clustering methods, the FCM algorithm is one of the most popular methods due to it can retain more information from the source (original) image and robust property for ambiguity. Fuzzy C-means (FCM) clustering algorithm works well on most of the noise free images.

Ahmed et al. proposed FCM_S where the objective function is modify to be influenced by the labels in its immediate neighbourhood. The computational complexity for the FCM_S is more as compared to FCM due to it computes the neighbourhood term in each iteration step. Cai et al. proposed the fast generalized fuzzy c-means (FGFCM) clustering algorithm is used to improve the clustering performance and to facilitate the choice of the

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neighbouring control parameter. The selection of parameter is not easy to implement due to there is no prior knowledge about the noise level [19]-[20].

Krindis and Chatzis proposed the fuzzy local information c-means clustering algorithm. The Fuzzy Local Information C-Means (FLICM) clustering algorithm which is insensitiveness to noise and image detail preservation [1]-[6]. The new factor in Fuzzy Local Information C-Means (FLICM) clustering algorithm is called fuzzy factor. The fuzzy factor is introduced into the object function of FLICM to modify the clustering performance. The features of the fuzzy factors are as follows,

a. Fuzzy factor which is insensitiveness to noise due to it contains the information about spatial context.
b. Fuzzy factor isn't contains any parameter selection.
c. Fuzzy factor generally use the original image avoids to reducing the noise that could cause detail missing.

The general formula for the fuzzy factor G_{ki} is given by,

$$G_{ki} = \sum_{\substack{j\in N_i,\\ i\neq j}} \frac{1}{d_{ij}+1}(1-u_{kj})^m ||x_j - v_k||^2 \qquad (6)$$

The objective functions for the Fuzzy Local Information C-Means (FLICM) clustering algorithm are as follows,

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c}[u_{ki}^m ||x_i - v_k||^2 + G_{ki}] \qquad (7)$$

Where v_k denotes the prototype value of the k^{th} cluster, u_{ki} denotes the fuzzy membership of the i^{th} pixel with respect to cluster *k*, N is the number of data items and c is the number of clusters. Finally, the Fuzzy Local Information C-Means (FLICM) clustering algorithm is given by,

1) Set the number of c cluster prototype, fuzzification parameter m and stopping condition ϵ.
2) Initialize the fuzzy partition matrix $U^{(0)}$
3) Set the loop counter b=0.
4) Calculate the cluster center is given by,

$$v_j^{(b)} = \frac{\sum_{i=0}^{N} u_{ki}^m x_i}{\sum_{i=0}^{N} u_{ki}^m} \qquad (8)$$

5) Calculate the cluster center is given by,

$$u_{ji}^{(b+1)} = \frac{1}{\sum_{j=1}^{c}\left(\frac{||x_i - v_k||^2 + G_{ki}}{||x_i - v_j||^2 + G_{ji}}\right)^{\frac{1}{(m-1)}}} \qquad (9)$$

6) If max { $U^{(b)} - U^{(b-)}$ }< ϵ then stop, otherwise set b=b+1 and goto step 4.

4. Experimental Work and Result

In this section, in order to validate the effectiveness of the proposed Optical image change detection method, we will show the performance of the proposed methods by presenting the numerical results on the data set.

The data set represents a section (1330 X 1358 pixels) of two Optical images with LISS-III sensor over an area near the city some part of the Aurangabad in May 2010 and Nov 2010, respectively. Therefore, the valley between Aurangabad and Jalna was selected as a test site for detecting flooded areas. LISS-III sensor (Linear Imaging Self-Scanning-III Sensor) generally having four bands such as two visible bands (Green and Red), one NIR band and one SWIR band. Visible band having spectrum range is 0.40-0.75 micrometer, NIR band having spectrum range is 0.75-1.33 micrometer and SWIR band having spectrum range is 1.3-3 micrometer. Radiometric resolution for this LISS-III Sensor is 7-bits. Revisit time or repetivity time for this LISS-III Sensor is 24-days. The spatial resolution for visible (two bands such as Green and Red) and NIR (one band) is 23.5 meter with a ground swath of 141 kms. The spatial resolution for SWIR (one band) is 70.5 meter with a ground swath of 148 kms.

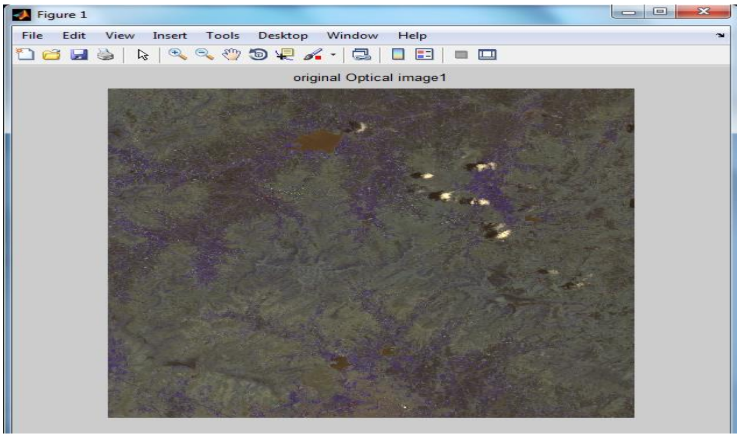

Figure 3. Original Optical Image 1

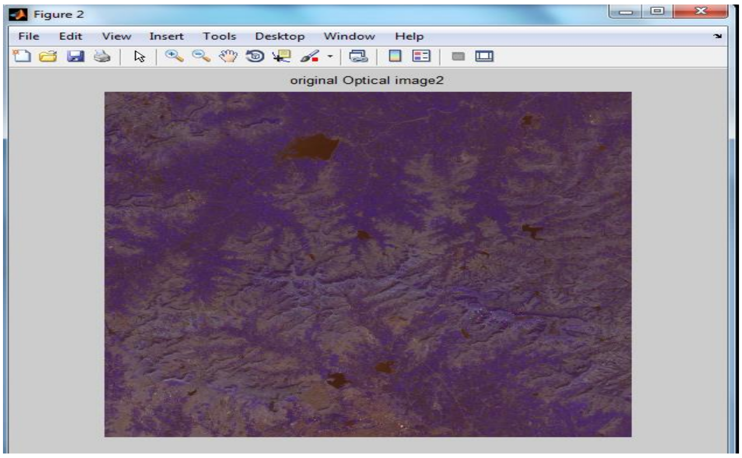

Figure 4. Original Optical Image 2

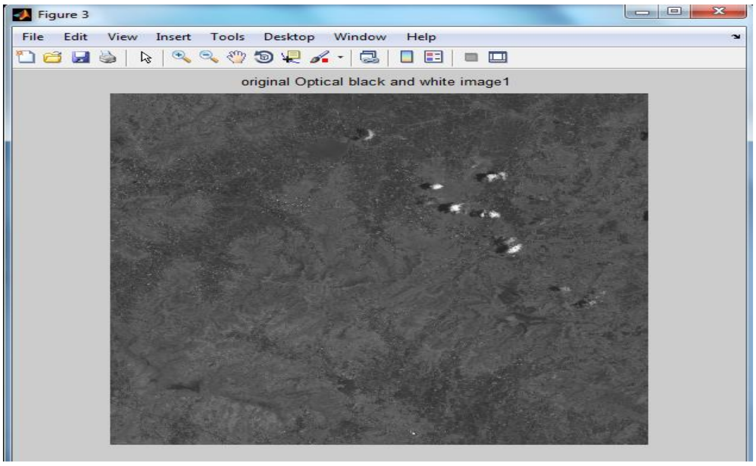

Figure 5. Original Optical black and white Image 1

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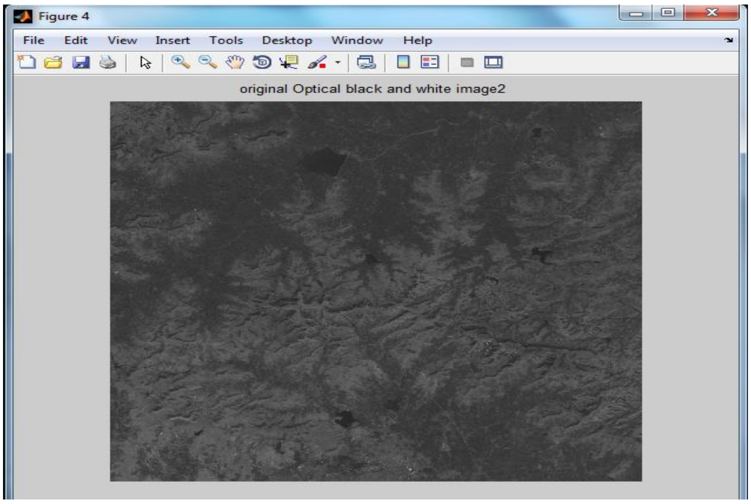

Figure 6. Original Optical black and white Image 2

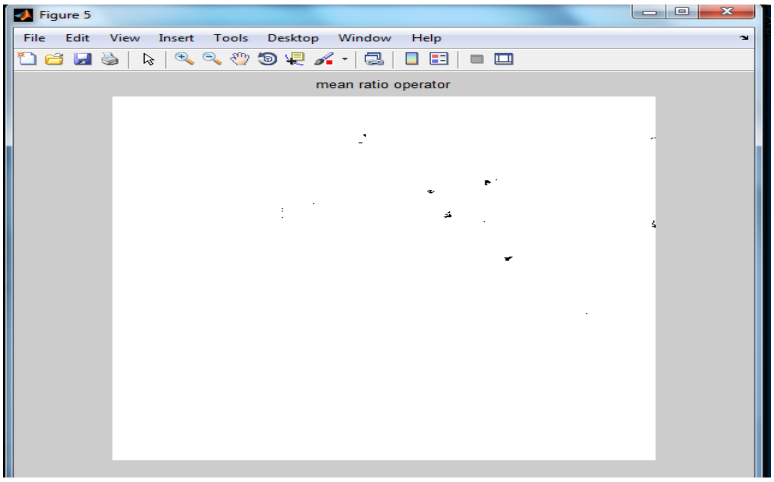

Figure 7. Mean ratio Operator

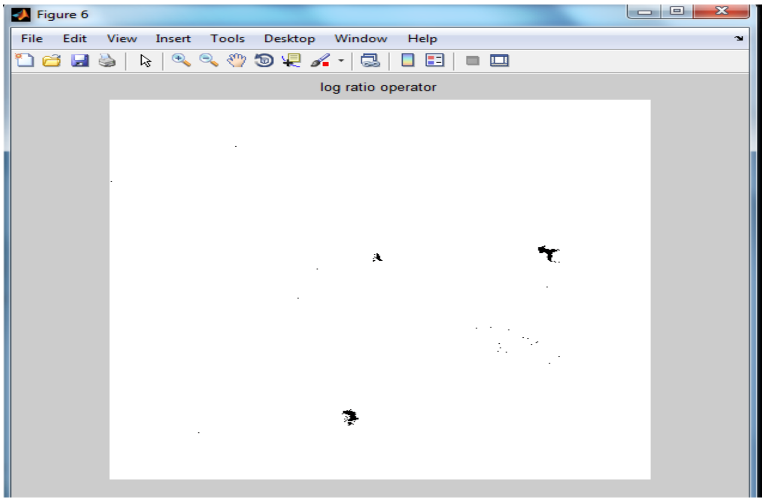

Figure 8. Log ratio Operator

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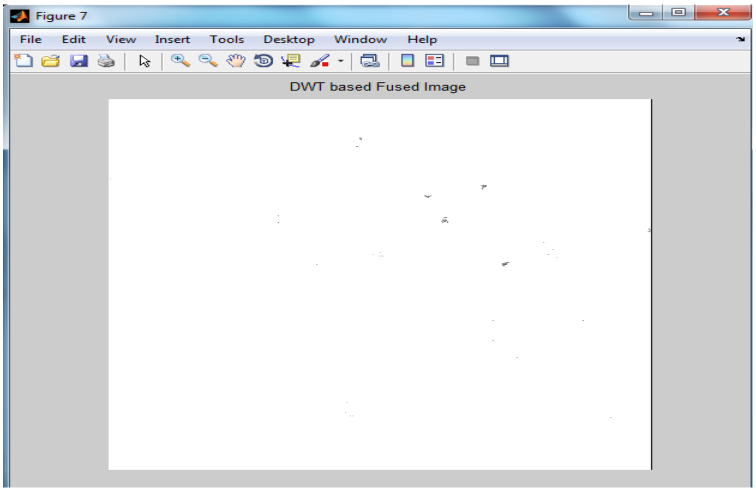

Figure 9. DWT based Fused Image

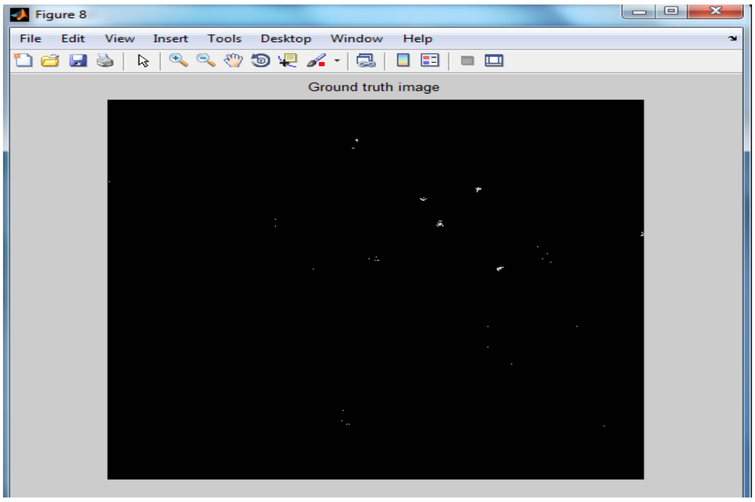

Figure 10. Ground Truth Image

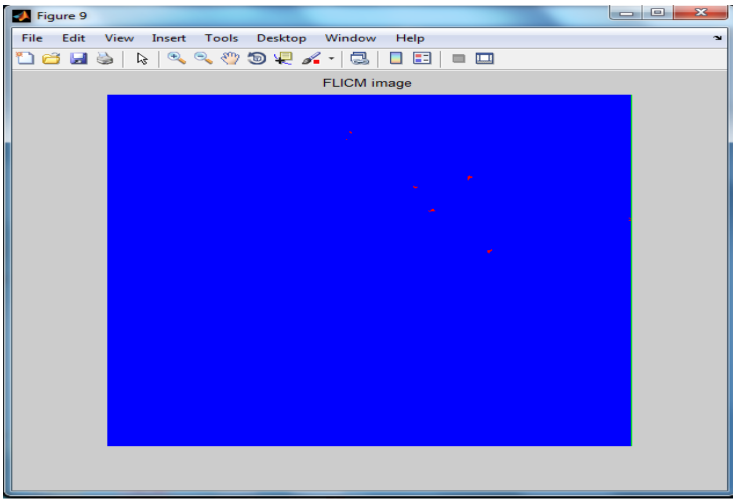

Figure 11. FLICM Image

Two experiments have been carried out i.e. purpose at difference image. The first experiment is purpose at the analysis of the effectiveness of the wavelet fusion strategy to generate the difference image. In addition, we compared the change detection performance of the algorithm with other two methods such as mean-ratio

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operator and log-ratio operator. K-means simple classification method is used to evaluate the change detection result that is obtained by the difference image. In the second experiment, we analyzed the impact of the FLICM algorithm onto the change detection result of the fused difference image [21].

The quantitative analyses of the change detection are as follows: First, we calculate the false negatives (FN, changed pixels that undetected). Second, we calculate the false positives (FP, unchanged pixels wrongly classified as changed). Third, we calculate the percentage correct classification (PCC) given by,

$$PCC = (TP+TN) / (TP+FP+TN+FN) \quad (10)$$

Here, TP means true positives, which is the number of pixels that are detected as the changed area in both reference images i.e. ground truth image and the result image. TN means true negatives, which is the number of pixels that are detected as the unchanged area in both reference images i.e. ground truth image and the result.

For the accuracy assessment, kappa statistics which is a measure of accuracy or agreement based on the difference between the error matrix and chance agreement [22]. If the change detection map and the ground truth image are in complete agreement then the kappa value is 1. If there is no agreement among the change detection map and the ground truth image then the kappa value is 0.

Total Iteration= 26

a) Mean-Ratio Technique

Predicted Classes	Actual Classes	
	0	1
1	221.00	3278.00
2	1800957.00	1684.00

Predicted Classes	Actual Classes	
	0	1
TP	221.00	1684.00
FP	3278.00	1800957.00
FN	1800957.00	3278.00
TN	1684.00	221.00
Preci.	0.06	0.00
Sensi.	0.00	0.34
Speci.	0.34	0.00

Table 1*: *Change Detection Results of the Aurangabad Data Set Obtained by Mean-Ratio Technique

b) Log-Ratio Technique

Predicted Classes	Actual Classes	
	0	1
1	2357.00	2922.00
2	1798821.00	2040.00

Predicted Classes	Actual Classes	
	0	1
TP	2357.00	2040.00
FP	2922.00	1798821.00
FN	1798821.00	2922.00
TN	2040.00	2357.00
Preci.	0.45	0.00
Sensi.	0.00	0.41
Speci.	0.41	0.00

Table 2*: *Change Detection Results of the Aurangabad Data Set Obtained by Log-Ratio Technique

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c) FLICM Technique

Predicted Classes	Actual Classes	
	0	1
1	1801178.00	2302.00
2	0.00	2660.00

Predicted Classes	Actual Classes	
	0	1
TP	1801178.00	2660.00
FP	2302.00	0.00
FN	0.00	2302.00
TN	2660.00	1801178.00
Preci.	1.00	0.00
Sensi.	1.00	0.54
Speci.	0.54	1.00

***Table 3**: Change Detection Results of the Aurangabad Data Set Obtained by FLICM Technique*

i) Performance Measures

Difference Image	PCC	Model Accuracy
Mean-Ratio	16.97%	0.00
Log-Ratio	20.62%	0.00
FLICM	76.80%	1.00

Table 4: Change Detection Results of the Aurangabad Data Set Obtained by K-means based on the Three Difference Image

ii) Kappa Statistics for FLICM

Cohen's kappa = 0.6974

Kappa error = 0.0063

Results on the Aurangabad data set:

The difference images generated by the two different methods such as mean-ratio, log-ratio have been shown in the above figure. As shown in above Table 4, the change detection results of the fused difference image were compared with the ones generate from mean-ratio operator, log –ratio operator and FLICM. It can be seen from the analysis of the PCC that, the change detection results of mean-ratio image, log-ratio image and FLICM that achieved by k-means method was disastrous. The PCC yielded by mean-ratio difference image, log-ratio difference image and FLICM difference image were equal to 16.97%, 20.62% and 76.80% respectively. FLICM difference image outperforms mean-ratio and log-ratio difference image. As can be concluded from analysis, the method that we proposed can effectively reduce the errors in the change detection results.

5. Conclusion

In this paper we have presented change detection approach for optical image based on the DWT image fusion technique and fuzzy clustering algorithm. The DWT image fusion approach that we proposed the key idea is to restrain the unchanged region information and to enhance the information of changed region in the greatest extent. Compared with the mean-ratio image and log-ratio image, the proposed approach such as FLICM clustering algorithm can reflect the real change trend and restrain the unchanged regions. Compared with the previous algorithm such as mean ratio operator, log-ratio operator and fuzzy c-means (FCM) clustering algorithm, FLICM is able to incorporate the local information more exactly. The experiment results show that the proposed FLICM strategy can integrate the advantage of the mean-ratio operator and log-ratio operator and gain a better performance.

The presented information constitutes a crucial purpose to begin for the addressing Research and Development within the area of the fuzzy clustering algorithm and DWT image fusion technique for change detection.

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References

[1] M. Gong, Z. Zhou and J. Ma, "Change detection in synthetic aperture radar images based on image fusion and fuzzy clustering," *IEEE Trans. Image Process.*, vol. 21, no.4, pp. 2141-2151, April 2012

[2] L. Paul and Dr. P. Ramamoorthy, "Synthetic aperture radar image change detection using fuzzy c-means clustering algorithm," *International Journal of Advanced Research in Computer and Communication Eng.*, vol. 2, Issue 3, pp,1374-1379, March 2013.

[3] S. Krinidis and V. Chatzis, "A robust fuzzy local information c-means clustering algorithm,"*IEEE Trans. Image Process.*, vol. 19, no. 5, pp. 1328-1337, May 2010.

[4] M. Gong, Y. Liang, J. Shi, W. Ma and J. Ma, "Fuzzy c-means clustering with local information and kernel metric for image segmentation," *IEEE Trans. Image Process.*, vol. 22, no. 2, pp. 573-584, Feb. 2013.

[5] S. K. Mekapothula, V. Jai Kumar, "An efficient algorithm for segmentation using fuzzy local information c-means clustering," *International Journal of Scientific and Eng. Research*, vol. 2, Issue 12, pp. 1-7, Dec. 2011.

[6] M. Prasad M. and Ravikumar A. V., "Robust technique for change detection in multitemporal synthetic aperture radar images," *International Journal of Scientific and Eng. Research*, vol. 4, Issue 7, July. 2013.

[7] W. Cai, S. Chen and D. Zhang, "Fast and robust fuzzy c-means clustering algorithm incorporating local information for image segmentation," *Pattern Recognit.*, vol. 40, No. 3, pp. 825-838, March 2007.

[8] R. J. Radke, S. Andra, O. Al-Kofahi and B. Roysam,"Image Change Detection Algorithms: A Systematic Survey," *IEEE Trans. Image process.*, vol. 14, no. 3, March. 2005.

[9] F. Bovolo and L. Bruzzone, "A detail-preserving scale-driven approach to change detection in multitemporal SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 12, pp. 2963-2972, Dec. 2005.

[10] S. Marchesi, F. Bovolo and L. Bruzzone, "A context-sensitive technique robust to registration noise for change detection in VHR multispectral images," *IEEE Trans. Image process.* vol. 19, no. 7, pp. 1877-1889, Jul. 2010.

[11] F. Bovolo, and L. Bruzzone, "A split-based approach to unsupervised change detection in large-size multitemporal images: application to Tsunami-Damage assessment," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 6, Jun. 2007

[12] E. Chuvieco, Fundamentals of satellite Remote Sensing, New York: CRC press.

[13] D. K. Salu and M. P. Parsai,"Different Image Fusion Techniques – A Critical Review," *International Journal of Modern Eng.Research*, vol.2, Issue 5, Sep.-Oct.2012.

[14] F. Galland, N. Bertaux and P. Refregier,"Minimum Description Length Synthetic Aperture Radar Image Segmentation," *IEEE Trans. Image process.*, vol. 12, no. 9, Sep. 2003.

[15] F. Chatelain, J. Y. Tourneret and J. Inglada,"Change Detection in Multisensor SAR Images Using Bivariate Gamma Distributions," *IEEE Trans. Image process.* vol. 17, no. 3, March. 2008.

[16] A. Robin, L. Moisan and S. L. Hegarat-Mascle,"An a-Contrario Approach for Sub-Pixel Change Detection in Satellite Imagery," *preprint* Map 5 no. 15, 2009.

[17] E. E. Kuruoglu and J. Zerubia,"Modelling SAR Images With a Generalization of the Rayleigh Distribution," *IEEE Trans. Image process.* vol. 13, no. 4, Apr. 2004.

[18] P. L. Rosin and E. Ioannidis,"Evalution of Global Image Thresholding for Change Detection," *Pattern Recognit. Lett.*, vol. 24, no. 14, pp. 2345-2356, Oct. 2003.

[19] C. Carincotte, S. Derrode and S. Bourenname,"Unsupervised Change Detection on SAR Images Using Fuzzy Hidden Markov Chains," IEEE *Trans. Geosci. Remote Sens.*, vol. 44, no. 2, Feb. 2006.

[20] M. Ayshu Ali and Dr. B. M. Imran,"Change Detection in SAR Images Using Contourlet," *International Journal of Scientific and Eng. Research*, vol. 4, Issue 8, Aug. 2013.

[21] M. Ganesh and V. Palanisamy,"A Modified Adaptive Fuzzy C-Means Clustering Algorithm for Brain MR Image Seg," *International Journal of Eng. Research and Technology*, vol. 1, Issue 8, Oct. 2012.

[22] A. Likas, N. Vlassis and J. J. Verbeek,"The Global K-Means Clustering Algorithm," *Pattern Recognit.., vol*. 24, no. 14, pp. 2345-2356, Oct. 2003.