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Local Edge Preserving Filter Based Image Fusion and Change Detection in SAR Images Using Fuzzy Clustering Algorithm

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Abstract*—*Change detection plays a vital role in overseeing the transformations on the earth surface. Due to the existence of speckle noise in SAR (Synthetic Aperture Radar) images, change detection becomes a challenging problem. Modified change detection in SAR images is proposed in this paper. It consists of four steps: Difference image generation using Gauss-log ratio operator and Log-ratio operator, image fusion using LEP (Local Edge Preserving) filter, image de-noising using Frost filter and to differentiate changed and unchanged regions in the fused image by using Reformulated Fuzzy Local Information C-Means (RFLICM)clustering. The proposed method is compared with Discrete Wavelet Transform (DWT) based change detection method using synthetic and real SAR images. The performances are evaluated by means of Overall Error (OE), Percentage Correct Classification (PCC), Kappa Coefficient (KC), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Segmentation Matching Factor (SMF). The results show that combination of gauss-log ratio operator and image fusion using LEP Filtering performs better than dwt based change detection.

Index Terms*— *change detection, gauss-log ratio, frost filter, local edge preserving (LEP), synthetic aperture radar (SAR).

I. INTRODUCTION

Change detection is a method that explores images obtained on the identical environmental area at diverse era to recognize changes that have occurred. Due to large number of applications in diverse fields such as remote sensing, video surveillance and medical diagnosis, change detection has attracted to various researches in recent years. Change detection in SAR images is challenging than optical images due to the presence of speckle noise. Change detection in SAR images consist of three steps such as 1) Difference image generation; 2) Image fusion; 3) Analysis of difference image. Subtraction operator and ratio-operator are widely known methods for difference generation. For SAR images, ratio operator is adapted due to calibration and radiometric errors [1]. By taking the ratio-operator, the multiplicative noise can be changed in to additive noise. Image Fusion is a method to obtain significant information from two or more images. Edges of the resultant image provided by previous fusion methods such as DWT, Contourlet, and Curvelets etc. are highly distorted and over-smoothed, which is not good for image fusion. In fuzzy clustering methods, Fuzzy C-Means (FCM) algorithm, which was the popular method used in image segmentation, but works only for most noise-free images.

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To improve the performance of image segmentation, FCM was modified as FCM_S and FGFCM by Ahmed *et al.* and Noordam [2], [3]. In order to balance between robustness to noise and to preserve details, a parameter was applied in the objective function. The selection of parameter was not easy, which leads to inaccurate results. Krindis and Chatzis had proposed a robust FLICM clustering algorithm as a remedy to all drawbacks [4]. FLICM is better in segmenting microarray spots compared to existing methods under the presence of noise [5]. This paper is organized as follows. Section II describes the existing change detection in SAR images using RFLICM. Section III provides proposed change detection approach. Section IV describes the datasets and parameters used. Section V describes results and discussions in synthetic and real SAR images and Section VI is the conclusion.

II. CHANGE DETECTION IN SAR IMAGES USING IMAGE FUSION AND FUZZY CLUSTERING

Let I_1 and I_2 be two images: $I_1 = \{I_1(i,j), 1 \le i \le m, 1 \le j \le n\}$ and, $I_2 = \{I_2(i,j), 1 \le i \le m, 1 \le j \le n\}$ taken over the same geographical area at two different times t_1 and t_2. The objective is to achieve a change map that depicts the changes between the two images I_1 and I_2. Change detection consists of three steps: Difference image generation using mean-ratio operator and log ratio operator, image fusion using Discrete Wavelet Transform, analysis of fused image using RFLICM is shown in Fig. 1. These three parts will be detailed as follows:

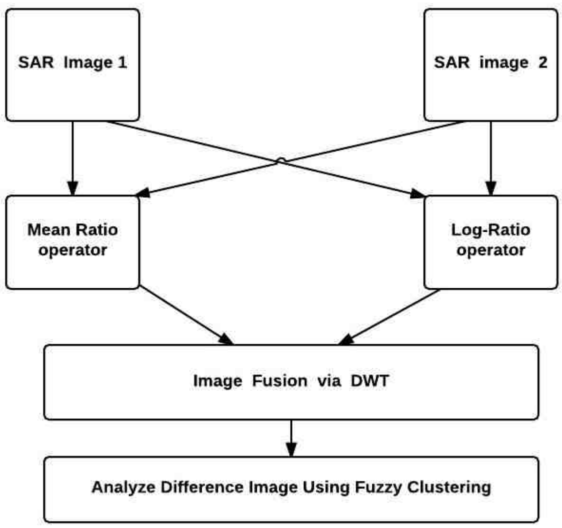

Fig. 1 Block diagram of existing change detection approach.

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A. Generation of difference Image via Mean-Ratio operator and Log -Ratio operator

Due to the presence of speckle noise, the ratio operator is expressed as a logarithmic or mean scale. The mean ratio operator assumes that a change portion in the scene modifies the local mean value of the SAR image. Mean ratio operator enhance high intensity pixels and weakens low intensity pixels, while log ratio operator enhance low intensity pixels and weakens high intensity pixels. So, the fused image obtained from mean-ratio operator and log-ratio operator provides better difference image.

Mean- ratio operator is given by

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

where μ_1 and μ_2 represent local mean values of two SAR images I_1 and I_2.

$$X_l = \left|\log \frac{X_2}{X_1}\right| = \left|\log X_2 - \log X_1\right| \tag{2}$$

where log stands for natural logarithm. Image fusion strategies are used to generate a better difference image from the two different images.

B. Image Fusion via Discrete Wavelet Transform (DWT)

The image fusion scheme based on the wavelet transform can be described as follows: First, compute the DWT of each of the two source images and obtain the multiresolution decomposition of each source image. Then, fuse the corresponding coefficients of the approximate and detail subbands of the decomposed source images using the developed fusion rule in the wavelet-transform domain. In particular, the wavelet coefficients are fused using different fusion rules for a low-frequency band and a high-frequency band, respectively. Finally, the inverse DWT is applied to the fused multiresolution representation to obtain the fused result image. Two main fusion rules are described as follows. The average operator is applied for low-frequency band is given by

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

The minimum local area energy is applied for high frequency band is given by

$$D_\varepsilon^F(i,j) = \begin{cases} D_\varepsilon^m(i,j), E_\varepsilon^m(i,j) \prec E_\varepsilon^l(i,j) \\ D_\varepsilon^l(i,j), E_\varepsilon^m(i,j) \ge E_\varepsilon^l(i,j) \end{cases} \tag{4}$$

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

where m and l represents mean-ratio image and log-ratio image, respectively. F denotes the new fused image. D_{LL} stands for low-frequency coefficients. $D_\varepsilon^F(i,j)$ (ε=*LH, HL, HH*) represents three high-frequency coefficients at point(*i, j*) in the corresponding subimages. $E_\varepsilon(i,j)$ represents the local area energy of the wavelet coefficient at point (*i, j*) in the corresponding subimage and $N_{i,j}$ represents the local window centered on (*i, j*). $D_\varepsilon(k)$ denotes the value of the wavelet coefficient that is around the local window.

C. Detect changed areas in the fused image using RFLICM

The purpose to process the fused image is to differentiate changed area from unchanged area. Analysis of the fused image is done by using RFLICM Clustering, which is a modification of FLICM. To enhance the clustering performance, a novel fuzzy factor is introduced in FLICM. This fuzzy factor incorporates local gray-level information and spatial information. The damping extent of neighbors can't be accurately calculated using spatial distance. So the spatial distance is replaced by local coefficient of variation in RFLICM. Thus the local coefficient of variation between neighboring pixels and central pixel is calculated in accordance with the gray level difference.

Objective function of RFLICM is defined as:

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[u_{ki}^m \left\|x_i - v_k\right\|^2 + G_{ki}^{'}\right] \tag{6}$$

where v_k represent the prototype value of k^{th} cluster and u_{ki} represent fuzzy membership of the i^{th} pixel with respect to cluster k. N is the number of pixels. m is the fuzzification parameter. c is number of clusters. $\|x_i - v_k\|^2$ is the euclidean distance between object x_i and v_k. $G_{ki}^{'}$ is the fuzzy factor. Fuzzy partition matrix is given by

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\left\|x_i - v_k\right\|^2 + G_{ki}^{'}}{\left\|x_i - v_j\right\|^2 + G_{ji}^{'}}\right)^{1/m-1}} \tag{7}$$

Cluster center is given by

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

$G_{ki}^{'}$ is the modified fuzzy factor is given by

$$G_{ki}^{'} = \begin{cases} \sum_{j \in N_i} \dfrac{(1-u_{kj})^m \left\|x_j - v_k\right\|^2}{2 + \min\left(\left(c_u^j / c_u\right)^2, \left(c_u / c_u^j\right)^2\right)} & \text{if } C_u^j \ge \overline{C_u} \\ \sum_{j \in N_i} \dfrac{(1-u_{kj})^m \left\|x_j - v_k\right\|^2}{2 - \min\left(\left(c_u^j / c_u\right)^2, \left(c_u / c_u^j\right)^2\right)} & \text{if } C_u^j < \overline{C_u} \end{cases} \tag{9}$$

where local coefficient of variation is given by

$$C_u = \frac{\operatorname{var}(x)}{\left(\bar{x}\right)^2} \tag{10}$$

where $\operatorname{var}(x)$ and $\bar{x}$ are the intensity variance and the mean in local window of the image. C_u is the local coefficient of variation of central pixel. C_u^j is the local coefficient of variation of neighboring pixels. $\overline{C_u}$ is the mean value of C_u^j that is located in local window. RFLICM Algorithm is given as follows:

1) Set the no of clusters c, fuzzification parameter m and stopping condition ε.

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2) Initialize randomly fuzzy partition matrix u_{ki} .
3) Set the loop counter b=0.
4) Calculate cluster center using the equation (8).
5) Calculate fuzzy partition matrix using the equation (7).
6) max $\{U^{(b)} - U^{(b+1)}\} < \varepsilon$ then stop; otherwise set b=b+1, and go to step 4.

III. Proposed Change Detection Method

A modified change detection in SAR image consists of four steps: 1) Difference image generation using Gauss-log ratio operator and log ratio operator; 2) Image fusion using LEP filter; 3) Image denoising using Frost Filter; 4)Analysis of fused image using RFLICM as shown in Fig.2. These four parts will be detailed as follows:

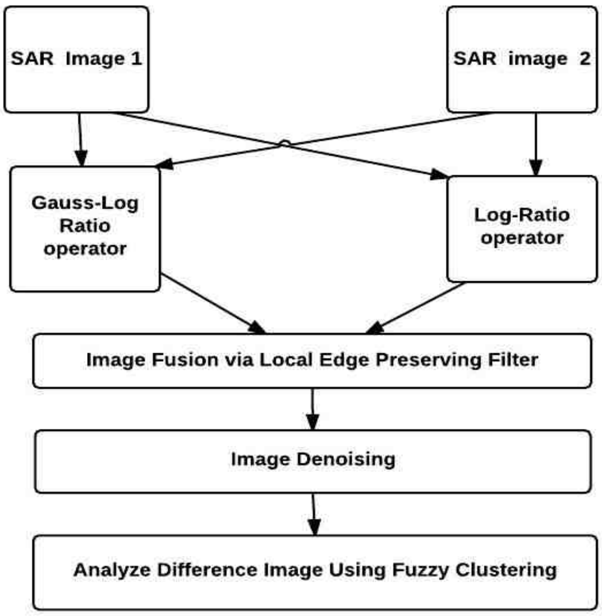

Fig. 2 Block diagram of the proposed change detection approach

A. Generation of difference Image via Gauss-Log Ratio operator and Log Ratio operator

The ratio operator is broadly used to obtain a different image. The Log-ratio operator usually converts linear scale of SAR data to a logarithmic scale and as a result transforms the multiplicative noise into additive noise [6]. In order to improve the real change trend as well as to restrain the unchanged portions in the difference image, the Gauss-log ratio operator is proposed. Gauss-log ratio operator is defined as follows:

$$X_{1r}(i,j) = \log(X_1^{'}(i,j)) * G \tag{11}$$

$$X_{2r}(i,j) = \log(X_2^{'}(i,j)) * G \tag{12}$$

$$X_r(i,j) = \sum_{m=-1}^{1}\sum_{n=-1}^{1}\left|X_{1r}(i+m,j+n) - X_{2r}(i+m,j+n)\right| \tag{13}$$

where $X_1^{'}(i,j)$ and $X_2^{'}(i,j)$ are two patches centered at point (i, j) in SAR image. G is a rotationally symmetric Gaussian low-pass filter of size 3×3 with standard deviation 0.5.

B. Image Fusion via Local Edge Preserving Filter

Image fusion refers to a technique to attain information of greater quality by means of complementary information from Gauss log ratio image and Log ratio image so that the new fused images are more suitable for the use of the computed processing tasks. The DWT provide detail information to be easily extracted from images. Compared with the DWT, transforms such as curvelets and contourlets are proved to have a better shift invariance property and directional selectivity. A novel image fusion method based on guided filtering utilizes the average filter to get the two-scale representations, which is simple and effective. This method is very robust to image registration and computationally efficient, making it quite fit for real applications [7]. A major drawback of guided filtering based image fusion is that it may over-smooth the resulting weights, which is not good for image fusion. To solve the above problem, an image fusion using LEP (Local Edge Preserving) filter is proposed. LEP filtering based image fusion gives much better performance when compared with other approaches [8]. Other advantages are, it is a fast two-scale fusion method which does not depend deeply on a specific image decomposition method. Pixel saliency and spatial context for image fusion are attained by novel weight construction method. In this technique the balance of pixel saliency and spatial consistency are acquired by the parameter adjustment of the LEP filter. Local Edge preserving Filter is exploited to develop an edge preserving analysis of an image. The local salient edges in the image are retained. The B has a linear dependence with I in a local window, since pixels are highly correlated locally. The local approximation of B is represented as:

$$B_i = a_w I_i + b_w, i \in w \tag{14}$$

$$a_w = \frac{\sigma_w^2}{\sigma_w^2 + \frac{1}{N}\alpha^{'}\sum_{i\in w}\left|\nabla I_j\right|^{2-\beta}} \tag{15}$$

$$b_w = \overline{I_w} - a_w \overline{I_w} \tag{16}$$

ie, B has a linear dependence with I in a local window, where a_w and b_w are constant coefficients represented in the window w. σ_w^2 is the variance of I in the window of w and I_w is the mean of I in w. If a local patch is recognized by the central pixel, then the a_w and b_w are changed to a_k and b_k where k is central pixel's location. The two parameters used in LEP are $\alpha^{'}$ and β. If these parameters are small, more gradient will be considered as salient edges. If they are large, the filtered outputs will be over smoothed. The parameters determine accuracy of the image. $\alpha^{'}=1$ and $\beta=1$ always preserve salient edges and produce excellent results. Then the output of the Local Edge Preserving Filter is

$$B_i^{'} = \frac{1}{N}\sum_{k\in w}(a_k I_i + b_k) = \overline{a_i} I_i + \overline{b_i}, i \in \Omega \tag{17}$$

where Ω is the area of the image and $\overline{a_i}$ represents mean of a_k in the neighbourhood patch and same for $\overline{b_i}$. The output $B_i^{'}$ and weight map is given to structural similarity system that gives structure of objects in the scene [12].

1. Algorithm for image fusion using LEP Filtering

The first step involved in the LEP filtering is to generate Two scale image decomposition of input images. The second step is based on the Local Edge Preserving filter,

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which is applied for the fusion of the base and detail layers. The last step is Two scale image reconstruction to get final fused output. Fig. 3 represents block diagram of Image fusion using Local Edge Preserving Filter

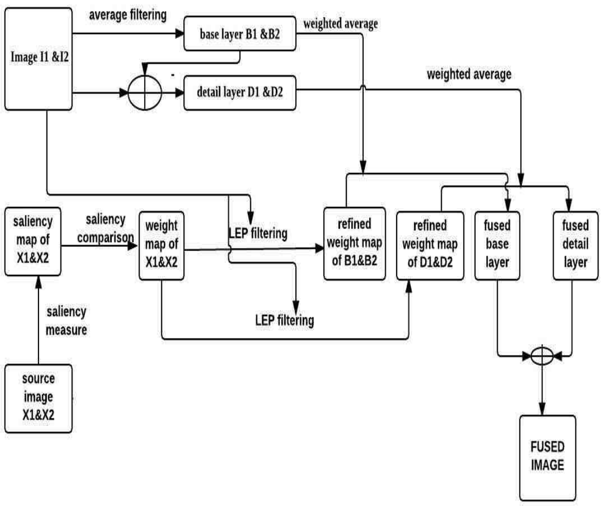

Fig. 3 Block diagram of Image fusion using Local Edge Preserving Filter

1.1 Two-Scale Image Decomposition

The source images are decomposed into base layer and detail layer. Base layer is obtained by applying average filtering to the source images. The base layer of source image is represented as:

$$B_n = I_n * Z \tag{18}$$

where I_n is the n^{th} image, Z is the average filter. Detail layer is obtained by subtracting the base layer from the source image. This is represented by:

$$D_n = I_n - B_n \tag{19}$$

1.2 Weight Map Construction via LEP Filtering

Weight map is constructed by following steps. First step is to attain a high-pass image H_n after applying Laplacian filtering, which is represented as:

$$H_n = X_n * L \tag{20}$$

where L is 3 X 3 Laplacian Filter and X_n be the source image. Second Step is to create a salient map S_n by using the local average of the absolute value of H_n. S_n is given by the equation

$$S_n = |H_n| * g_{r_g,\sigma_g} \tag{21}$$

where g represents a Gaussian low-pass filter which has size $(2r_g+1)$ $(2r_g+1)$, r_g and σ_g are set to 5.The Salient map generated gives an excellent portrayal of detail information of the saliency level. Third Step is to determine weight maps by comparing the salient maps generated in a second step. Comparison is done by following steps:

$$P_n^k = \begin{cases} 1 & if\ S_n^k = \left(S_1^k, S_2^k, \ldots, S_N^k\right) \\ 0 & otherwise \end{cases} \tag{22}$$

where N gives the number of source image, S_n^k is the salient value of k^{th} pixel in the n^{th} image. Resultant fused image contains artifacts due to the noise and unaligned object boundaries in the weight map. Former optimization methods are inefficient to solve the problem, so LEP filter is proposed. LEP filter takes weight map P_n and source image I_n, which serves as guidance image. The Resultant weight map of the base layer and the detail layer are given by

$$W_n^B = LEP(P_n, I_n) \tag{23}$$

$$W_n^D = LEP(P_n, I_n) \tag{24}$$

1.3 Two-Scale Image Reconstruction

Fused image F is created from fused base layer and fused detail layer. Fused base layer and detail layer are created from weighted average method. The Fused base layer and detail layer are given by

$$\overline{B} = \sum_{n=1}^{N} W_n^B B_n \tag{25}$$

$$\overline{D} = \sum_{n=1}^{N} W_n^D D_n \tag{26}$$

The Final Fused image is given by

$$F = \overline{B} + \overline{D} \tag{27}$$

C. Image de-noising using Frost Filter

The frost filter is implemented to reduce noise and it is computationally very efficient [10]. In addition to its use for smoothing noisy radar images, the frost filter can also be used for processing images that are degraded by a multiplicative noise. The pixel being filtered is replaced with a value calculated based on the distance from the filter center [11].

D. Detect changed areas in the fused image using RFLICM

The analysis of the fused image is done by using RFLICM Clustering. The spatial distance fails to analyze the impact of each neighboring pixels on the fuzzy factor [9]. So the spatial distance is replaced by local coefficient of variation.

IV. DATASETS DESCRIPTION AND PARAMETER SETTING

In order to validate the effectiveness of the proposed change detection method, five set of synthetic images and three sets of real SAR images are considered. Different parameters are introduced for evaluation criteria.

A. Datasets

Five set of synthetic images are generated for evaluation. For real images, first data set represent two SAR images of Great Salt Lake acquired by Landsat satellite in 1985 and 2010. Second set contains two SAR images obtained by Landsat satellite showing the Aral Sea in Uzbekistan and Kazakhstan in 1999 and 2001. And third set comprise of two SAR images taken over the city of Istanbul acquired by RADARSAT satellite in 1975 and 2011.

B. Parameters Used

The performance of the proposed method is compared with existing method with respect to the parameters such as OE, PCC, KC, MSE, PSNR and SMF.

1. Overall Error (OE)

The overall error (OE) is defined as the percentage of sum of false positive and false negative, which can be calculated as:

$$OE = \left[\frac{(FP + FN)}{N}\right] * 100 \tag{28}$$

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where *FP* (False Positive) is defined as the number of pixels belonging to the unchanged class but falsely classified as changed class, the *FN* (False Negative) is defined as the number of pixels belonging to the changed class but falsely classified as unchanged class and *N* be the number of entire pixels.

$$N = TP + TN + FP + FN \tag{29}$$

$$TP = N_c - FN \tag{30}$$

$$TN = N_u - FP \tag{31}$$

N_c is the actual number of pixels belonging to the changed class and N_u is the actual number of pixels belonging to the unchanged class.

2. Percentage Correct Classification (PCC)

The percentage correct classification (*PCC*) is the percentage of sum of true positive and true negative, which is calculated as:

$$PCC = \left[\frac{(TP + TN)}{N}\right] * 100 \tag{32}$$

3. Kappa coefficient (KC)

The Kappa coefficient (*KC*) is defined as:

$$KC = \left[\frac{(PCC - PRE)}{(1 - PRE)}\right] \tag{33}$$

$$PRE = \frac{\left[(TP + FP).N_c + (FN + TN).N_u\right]}{N^2} \tag{34}$$

The value of *KC* ranges from 0 to 1.

4. Mean Square Error (MSE)

The Mean Square Error (*MSE*) can be calculated a

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[I(i, j) - K(i, j)\right]^2 \tag{35}$$

where *K* is the segmented output image and *I* be the reference image.

5. Peak Signal to Noise Ratio (PSNR)

The parameter PSNR can be defined as:

$$PSNR = 10log\left(\frac{MAX_I^2}{MSE}\right) \tag{36}$$

where MAX_I is the maximum possible pixel value of image.

6. Segmentation Matching Factor (SMF)

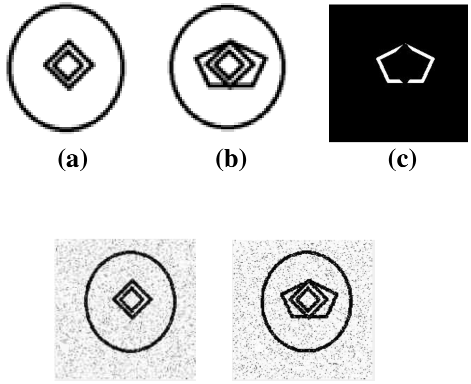
The Segmentation Matching Factor (SMF) is defined as

$$SMF = \sum_{i=1}^{c} \frac{A_i \cap A_{ref}}{A_i \cup A_{ref}} \tag{37}$$

where c is the number of clusters, A_i represents the set of pixels belonging to the i^{th} class in the segmented output image. A_{ref} represents the set of pixels belonging to the i^{th} class in the reference image.

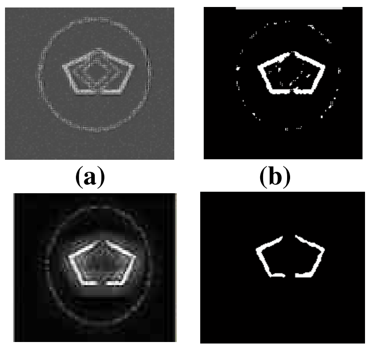
V. Results And Discussion

The efficiency of the proposed method is evaluated on real and synthetic images, which are corrupted by different levels of noise. The performances are evaluated by means of OE, PCC, KC, MSE, PSNR and SMF. Salt & pepper noise of different noise density levels (d) are added to each set of synthetic image. Table I shows the values of different evaluation criteria applied on a synthetic image, corrupted by salt & pepper noise. Speckle noise of different values of variances (v) and additive white gaussian noise (awgn) of different signal to noise ratio (snr) are also added to each set of synthetic image. Table II and Table III shows the values of speckle noise and awgn, respectively. Each synthetic image are corrupted by different levels of noise and is tested five times on the dwt based change detection method (Existing) method and proposed method, and the average is taken as result. Original images are shown in Fig. 4(a) and 4(b). Fig. 4(c) shows the difference image. Fig. 4(d) and Fig. 4(e) are the original images corrupted by salt & pepper noise (d=0.10). In the existing method, image fusion using DWT generates difference image from mean-ratio operator and log-ratio operator. The mean ratio operator cannot completely reflect



(a) (b) (c) (d) (e)

Fig. 4 (a) Original image I_1 (b) Original image I_2 (c) Difference image (d) Image I_1 with salt & pepper noise (d=0.10) (e) Image I_2 with salt & pepper noise (d=0.10).



(a) (b) (c) (d)

Fig. 5 (a) Result of DWT based image fusion (b) Result of RFLICM Clustering (c) Result of image fusion using LEP filter (d) Result of RFLICM Clustering.

the real change trends. The changed regions and its edges in the fused image are not clear. Fig. 5(a) shows the result of DWT based image fusion. Fig. 5(b) shows the result of RFLICM Clustering. In order to enhance the changed regions and edges of the fused image, LEP based image fusion is proposed. LEP based image fusion generates difference image from gauss-log ratio operator and log-ratio operator. The gauss-log ratio operator enhances and preserves the

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homogeneity of the real changed portions and suppresses the unchanged portions in the difference image. In LEP based image fusion, input images are broken down in to a two-scale image representation with a base layer having large scale variations in intensity, and a detail layer containing small scale details. It produces fast and effective image fusion method for creating high quality fused images by merging component images. It also preserves most of the useful information of component images including the edges. Fig 5(c) shows the result of image fusion using LEP filter. Fig. 5(d) shows the result of RFLICM Clustering.

Table–I: Values of the evaluation criteria of the synthetic dataset which are affected by salt & pepper noise.

Salt & Pepper (d=0.05)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	2.58	97.41	0.63	0.025	64.00	47.98
Proposed	0.30	99.69	0.93	0.003	73.32	87.65
Salt & Pepper (d=0.10)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	2.93	97.06	0.61	0.029	63.45	45.47
Proposed	0.40	99.59	0.90	0.004	72.02	82.52
Salt & Pepper (d=0.15)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	3.58	96.41	0.56	0.035	62.58	41.03
Proposed	1.07	98.92	0.68	0.010	67.81	52.64
Salt & Pepper (d=0.20)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	4.41	95.59	0.51	0.044	61.68	36.54
Proposed	1.16	98.83	0.65	0.011	67.47	48.90

Table I shows that the proposed method has highest PCC, KC, PSNR, SMF and lowest OE, MSE values compared with the existing method for all levels of salt & pepper noise. The PCC, KC, PSNR and SMF values of the proposed method are increased by 2.64%, 0.21, 7.22 dB and 25 compared to existing change detection method. The OE and MSE values are decreased by 2.64% and 0.026, respectively. So the proposed method is better compared with the existing method. Original images are shown in Fig. 6(a) and 6(b). Fig 6(c) shows the difference image. Fig. 6(d) and Fig. 6(e) are the original images corrupted by speckle noise. In the existing method, image fusion using DWT generates difference image from mean-ratio operator and log-ratio operator.

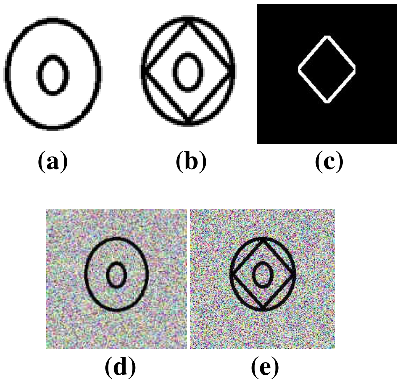

Fig. 6 (a) Original image I_1 (b) Original image I_2 (c)Difference image (d) Image $I_1$with speckle noise (v=0.45) (e) Image I_2 with speckle noise (v=0.45)

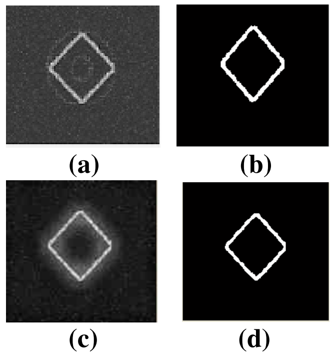

Fig. 7 (a) Result of DWT based image fusion (b) Result of RFLICM Clustering (c) Result of image fusion using LEP filter (d) Result of RFLICM Clustering.

The mean ratio operator cannot completely reflect the real change trends .The changed regions and its edges in the fused image are not clear. Fig. 7(a) shows the result of DWT based image fusion. Fig. 7(b) shows the result of RFLICM Clustering. In order to enhance the changed regions and edges of the fused image, LEP based image fusion is proposed. LEP based image fusion generates difference image from gauss-log ratio operator and log-ratio operator. The gauss-log ratio operator enhances and preserves the homogeneity of the real changed portions and suppresses the unchanged portions in the difference image. In LEP based image fusion, input images are broken down in to a two-scale image representation with a base layer having large scale variations in intensity, and a detail layer containing small scale details. It produces fast and effective image fusion method for creating high quality fused images by merging component images. It also preserves most of the useful information of component images including the edges. Fig. 7(c) shows the result of image fusion using LEP filter. Fig. 7(d) shows the result of RFLICM Clustering.

Table- II: Values of the evaluation criteria of the synthetic dataset which are affected by speckle noise.

Speckle noise (v=0.25)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	2.85	97.15	0.675	0.028	63.58	52.61
Proposed	0.15	99.85	0.97	0.001	76.36	95.21
Speckle noise (v=0.35)						
	OE (%)	PCC (%)	KC	MSE	PSNR (dB)	SMF
Existing	2.87	97.13	0.674	0.028	63.55	52.50
Proposed	0.18	99.81	0.968	0.001	75.45	94.07

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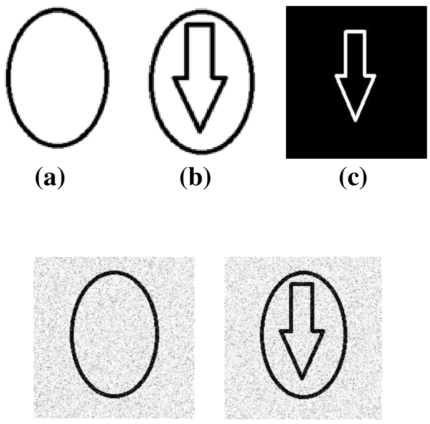
Speckle noise (v=0.45)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	2.88	97.12	0.671	0.028	63.53	52.15
Proposed	0.22	99.77	0.961	0.002	74.56	92.73
Speckle noise (v=0.55)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	2.90	97.09	0.668	0.029	63.49	51.78
Proposed	0.39	99.60	0.930	0.003	72.16	87.31

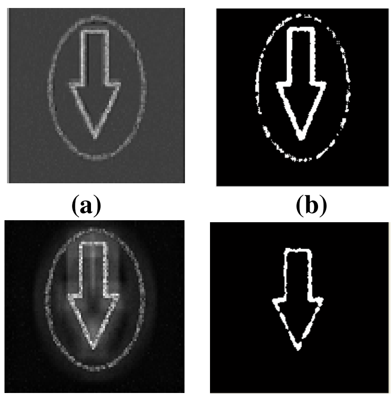
Table II shows that the proposed method has highest PCC, KC, PSNR, SMF and lowest OE, MSE values compared with the existing method with different variances of speckle noise. The PCC, KC, PSNR and SMF values of the proposed method are increased by 2.6%, 0.28, 11dB and 40. The OE and MSE values are decreased by 2.64% and 0.026, respectively. So the proposed method is better compared to the existing method. The synthetic image is also corrupted by additive white gaussian noise (awgn) with different signal to noise ratio (snr). Original images are shown in Fig. 8(a) and Fig. 8(b). Fig. 8(c) shows the difference image. Fig. 8(d) and Fig. 8(e) are the original images corrupted by additive white gaussian noise (snr=15).



(a) (b) (c)

(d) (e)

Fig. 8 (a) Original image I_1 (b) Original image I_2 (c) Difference image (d) Image I_1 with awgn (snr=15) (e) Image I_2 with awgn (snr=15).



(a) (b)

(c) (d)

Fig. 9 (a) Result of DWT based image fusion (b) Result of RFLICM Clustering (c) Result of image fusion using LEP filter (d) Result of RFLICM Clustering.

In existing method, image fusion using DWT generates difference image from mean-ratio operator and log-ratio operator. The mean ratio operator cannot completely reflect the real change trends .The changed regions and its edges in the fused image are not clear. Fig. 9(a) shows the result of DWT based image fusion. Fig. 9(b) shows the result of RFLICM Clustering. In order to enhance the changed regions and edges of the fused image, LEP based image fusion is proposed. LEP based image fusion generates difference image from gauss-log ratio operator and log-ratio operator. The gauss-log ratio operator enhances and preserves the homogeneity of the real changed portions and, suppresses the unchanged portions in the difference image. In LEP based image fusion, input images are broken down in to a two-scale image representation with a base layer having large scale variations in intensity, and a detail layer containing small scale details. It produces fast and effective image fusion method for creating high quality fused images by merging component images. It also preserves most of the useful information of component images including the edges. Fig 9(c) shows the result of image fusion using LEP filter. Fig. 9(d) shows the result of RFLICM Clustering.

Table -III: Values of the evaluation criteria of the synthetic dataset which are affected by Additive white Gaussian noise (awgn).

Additive white Gaussian noise (snr=5)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	7.33	92.66	0.47	0.073	59.47	34.25
Proposed	1.74	98.25	0.69	0.017	65.71	54.34
Additive white Gaussian noise (snr=7)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	6.60	93.39	0.50	0.066	59.93	36.89
Proposed	1.58	98.41	0.71	0.015	66.12	57.18
Additive white Gaussian noise (snr=10)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	5.90	94.09	0.53	0.059	60.41	39.39
Proposed	1.20	98.79	0.79	0.012	67.32	67.34
Additive white Gaussian noise (snr=15)						
	OE (%)	**PCC (%)**	**KC**	**MSE**	**PSNR (dB)**	**SMF**
Existing	4.58	95.41	0.60	0.045	61.51	45.46
Proposed	1.03	98.97	0.83	0.010	68.00	72.19

Table III shows that the proposed method has highest PCC, KC, PSNR, SMF and lowest OE, MSE values compared with the existing method with different signal to noise ratio of additive white gaussian noise. The PCC, KC, PSNR, SMF values of the proposed method are increased by 4.71%, 0.23, 6.45 dB and 23. The OE and MSE values are decreased by 4.7% and 0.04, respectively. So the proposed method is better compared to the existing method. The change detection results of two SAR images over the Great Salt Lake, U.S in 1985 and 2010 are shown in Fig. 10. Fig. 11 illustrates the change detection results of two SAR images obtained by Landsat satellite showing the Aral Sea in Uzbekistan and Kazakhstan in 1999 and 2001. And Fig. 12 shows the change detection results of two SAR images taken over the city of Istanbul, acquired by ERS–2 (European Remote Sensing) satellite in 1975 and 2011.

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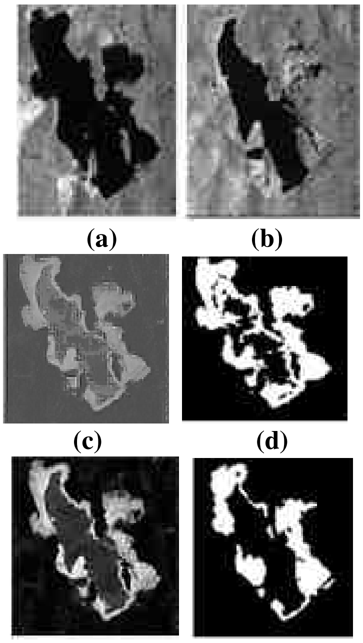
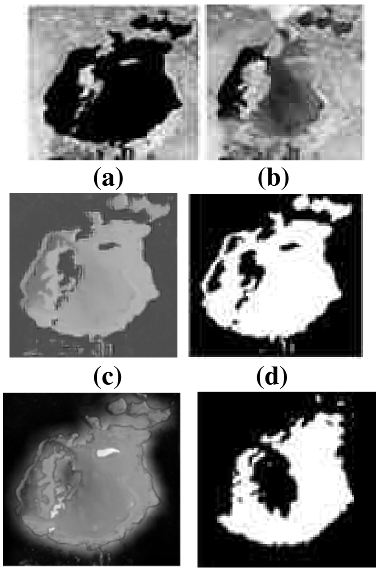


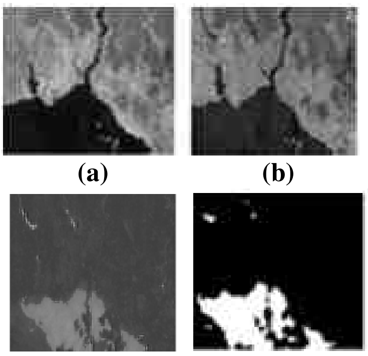
(a) (b) (c) (d) (e) (f)

Fig 10 (a) Original image I_1, acquired in1985 (b) Original image I_2, acquired in 2010 (c) Result of DWT based image fusion (d) Result of RFLICM Clustering (e) Result of LEP filter based image fusion (f) Result of RFLICM Clustering.

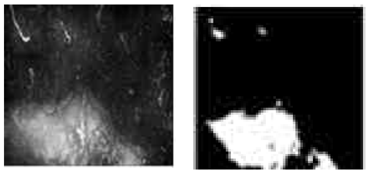


(a) (b) (c) (d) (e) (f)

Fig 11 (a) Original image I_1, acquired in1999 (b) Original image I_2, acquired in 2001 (c) Result of DWT based image fusion (d)Result of RFLICM Clustering (e) Result of LEP filter based image fusion (f) RFLICM Clustering.



(a) (b) (c) (d)



(e) (f)

Fig. 12 (a) Original image I_1, acquired in1975 (b) Original image I_2, acquired in 2011 (c) Result of DWT based image fusion (d)Result of RFLICM Clustering (e) Result of LEP filter based image fusion (f)Result of RFLICM Clustering.

VI. CONCLUSION

In this paper, a modified change detection in SAR image based on Gauss-log ratio operator and image fusion using LEP filter has been presented. The proposed Gauss-log ratio operator can enhance the information of the changed portion in the difference image. The Image fusion using Local edge preserving (LEP) filter provides a method to reduce noise and to preserve edges**.** The Frost filter is implemented to reduce multiplicative noise and is computationally very efficient. Finally, the RFLICM is applied to detect the changed and unchanged regions. The proposed method is tested on both synthetic and real images. The evaluation results shows that the proposed approach is better compared with dwt based change detection method.

REFERENCE

[1] E. J. M. Rignot and J. J. Van Zyl, "Change detection techniques for ERS-1 SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 31, no. 4, pp. 896–906, Jul. 1993.

[2] W. Cai, S. Chen, and D. Zhang, "Fast and robust fuzzy C-means clustering algorithms incorporating local information for image segmentation," *Pattern Recognit.*, vol. 40, no. 3, pp. 825–838, Mar. 2007.

[3] Biju V. G. , and P. Mythili. "A Genetic Algorithm based Fuzzy C Mean Clustering Model for Segmenting Microarray Images." *International Journal of Computer Applications* 52.11 (2012): 42-48.

[4] 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.

[5] Biju V. G. , and P. Mythili, "Fuzzy Clustering Algorithms for cDNA Microarray Image Spots Segmentation." *Procedia Computer Science* 46 (2015): 417-424.

[6] Biao Hou, Qian Wei, Yaoguo Zheng, and Shuang Wang, "Unsupervised Change Detection in SAR Image Based on Gauss-Log Ratio Image Fusion and Compressed Projection," IEEE journal of selected topics in applied earth observations and remote sensing, vol. 7, no. 8, August 2014.

[7] Shutao Li, " Image Fusion with Guided Filtering" Image Processing, IEEE Transactions on, vol. X, no. X, January 2013

[8] Bo,Gu, " Local Edge-Preserving Multiscale Decomposition for High Dynamic Range Image Tone Mapping"IEEE Transactions on, vol. 22, no. I, January 2013.

[9] M. Gong, Z. Zhou, and J. Ma, "Change detection in synthetic aperture radar images based on image fusion and fuzzy clustering," Image Processing, IEEE Transactions on, vol. 21, no. 4, pp. 2141–2151, 2012.

[10] Zhenghao Shi and Ko B. Fung, "A Comparison of Digital Speckle Filters," *Proceedings of IGARSS 94*, August 8-12, 1994, pp. 2129-2133

[11] Sivakumar, Member IACSIT, 2M. K. Gayathri and 3D. Nedumaran, *Member IEEE, IACSIT* "Speckle Filtering of Ultrasound B-Scan Image -A Comparative Study of Single Scale SpatialAdaptive Filters, Multiscale Filter and Diffusion Filters" Vol.2, No.6, December 2010.

[12] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, "Image quality assessment: from error visibility to structural similarity," IEEE Trans. Image Processing., vol. 13, no. 4, pp. 600–612, Apr. 2004.