

Recognition of Changes in SAR Images using Modified MRF Energy Function in FCM

S. Abirama Sundari
Electronics and Communication
B.S.Abdur Rahman University
Chennai, India

R. Iniyavan
Electronics and Communication
B.S.Abdur Rahman University
Chennai, India

Abstract-- In this world of rapid improvement in technology, we require an unsupervised method of global importance which would help us in continuous monitor of the available resources. So that we can use it more wisely to monitor the location of the resources over the time. In this paper we provide an contemporary approach to supervise the feasible resources using unsupervised detection in changes of synthetic aperture radar (SAR) images. Which is based on an image fusion method which includes novel fuzzy clustering mean, fuzzy local information clustering mean, reformulated fuzzy local information clustering mean, Markov random field algorithms. Synthetic aperture radar (SAR) images which is usually high in speckle noise. So Speckle reducing anisotropic diffusion filter is used to minimize effect of speckle noise. Image fusion method is used to generate a changed and unchanged region of SAR images using reciprocal information from a mean-ratio image and a log-ratio image.

Keywords: Fuzzy clustering algorithm, Markov random field, speckles reducing anisotropic diffusion, synthetic aperture radar (SAR).

I. INTRODUCTION

Image change detection is a process of detecting the image of same scene taken at different times in order to identify the changes in the images. It is used in various applications like medical diagnosis, remote sensing. SAR is usually implemented by mounting, on a moving platform such as an aircraft or spacecraft, a single beam-forming antenna from which a target scene is repeatedly illuminated with pulses of radio waves at wavelengths anywhere from a meter down to millimeters. Many echo waveforms received successively at different antenna positions are coherently detected and stored and then post-processed together to resolve the elements in an image of target region. However Synthetic aperture radar (SAR) image are striking and they are self-sufficient of atmospheric and sunlight condition, but they are affected by speckle noise.

II. SYSTEM MODEL

In general, change detection is a method of analysing the distorted and unaffected region of same geographical area taken at different times. Unsupervised change detection in SAR images can be alienated in to three steps image pre-

processing; producing dissimilarity image among the multi temporal images; and analysis of the difference image.

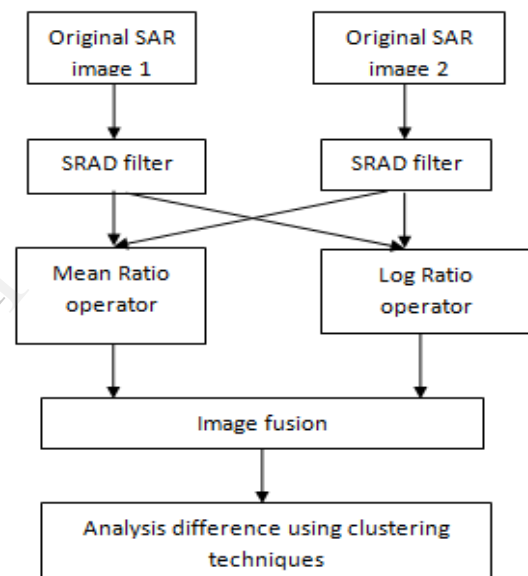


Fig (1)Proposed Block diagram

As shown in fig1 Let us consider two SAR images acquired over the same geographical area at different times, where 1 and 2 represents the different times. Speckle reducing anisotropic diffusion filter is applied two both the SAR images separately in order to smoothen the images, then it generates the difference image using stationary wavelet transform based on mean ratio image and log ratio image. And it repeated analysis the fused image by using different clustering techniques.

SPECKLE REDUCING ANISOTROPIC DIFFUSION FILTER

The speckle reduction is an important problem in synthetic aperture radar image which is edge sensitive and non additive process and the reduction of speckle noise without blurring the image is known to be complicated. An anisotropic directional filter that adapts to the propinquity and direction of nearby significant characteristics. In order to remove the speckle noise without blurring the image so

the position and path of edges in the image are estimated .then for each pixel in the image the distance and angle are estimated. In the presence of speckle noise, speckle reducing anisotropic diffusion excels over the conventional speckle removal filters and over the predictable anisotropic diffusion method in terms of mean preservation, variance reduction, and edge localization. The partial differential equation for diffusion is represented as

$$\frac{\partial I}{\partial t} = \text{div}[C(|\nabla I |), \nabla I] \quad (1)$$

Where ∇ represents gradient operator, I_0 is the initial image is known as diffusion tensor.

$$C(x) = 1 / (1+(x/k)^2) \quad (2)$$

Where K is constant depends upon the application.

IMAGE FUSION BASED ON SWT

The stationary wavelet transform (SWT) is a wavelet transform algorithm is designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor $2^{(j-1)}$. The SWT is an inherently redundant; the output of each level of SWT contains the same number of samples as the input. Modify the filter at each level by padding them with zeroes. The SWT is mainly used in the application of signal denoising and pattern recognition.

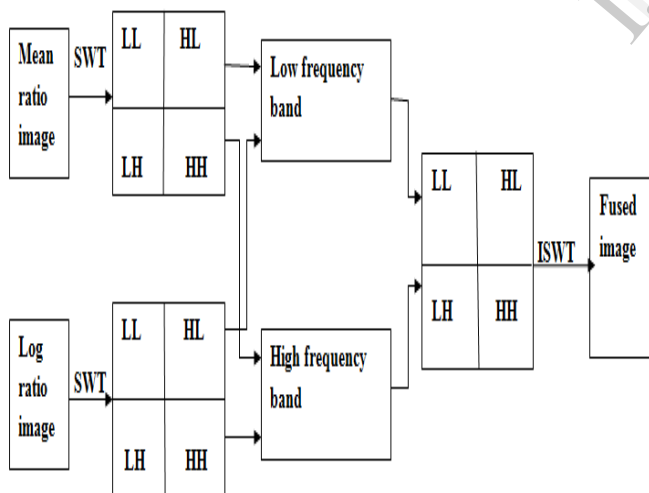


Fig (2) Image fusion based on SWT

The image fusion is obtained from mean ratio image(S_m) and log ratio image (S_l). both the image is decomposed separately by stationary wavelet transform .the corresponding frequency band is fused to together such as low frequency band and high frequency band. The sub band is clustered together and is decomposed .finally we obtain a fused image applying inverse stationary wavelet transform.

$$S_m = 1 - \min(\mu_1 / \mu_2, \mu_2 / \mu_1) \quad (3)$$

$$S_l = |\log X_2 - \log X_1| \quad (4)$$

Where μ_1 and μ_2 denotes the local mean value of SAR image respectively.

In fig 2 L and H denotes low pass and high pass filter. In accumulation HH, HL, LH represents diagonal, vertical, horizontal portion of the image and LL represents the estimated portion of the image. After one level of decomposition mean ratio image and log ratio image is decomposed in to four image as the original size which contains one low frequency sub band and three high frequency sub bands. Thus it restrain the unchanged region and enhance the changed region of the image.

$$D_{LL}^F = D_{LL}^m + D_{LL}^l \quad (5)$$

$$D_{\epsilon}^F(i,j) = \begin{cases} D_{\epsilon}^m(i,j), E_{\epsilon}^m(i,j) < E_{\epsilon}^l(i,j) \\ D_{\epsilon}^l(i,j), E_{\epsilon}^m(i,j) > E_{\epsilon}^l(i,j) \end{cases} \quad (6)$$

The equations (5) and (6) are used for selecting average value for low frequency band and minimum local area energy coefficient for high frequency band. in the equations m represents the mean ratio image and l represents the log ratio image . ϵ denotes HH HL LH three high frequency band.

$$E_{\epsilon}(i,j) = \sum_{k \in N_{i,j}} [D_{\epsilon}(k)^2] \quad (7)$$

Equation (7) is used to compute the local area energy coefficients. N_{ij} represents the local window centred on (i,j) , $D_{\epsilon}(k)$ denotes the value around the local window of the k th wavelet coefficient and $E_{\epsilon}(i,j)$ denotes wavelet coefficient at point (i,j) of the local area energy.

CLUSTERING

Clustering is the process of dividing the element in to cluster or object, so that it belongs to same classes or different classes. It depends upon the application which the cluster is been used, the element which belong to different classes must have similar measures such as distance, connectivity and intensity. There are two types of clustering they are hard clustering and soft clustering. In hard clustering each data element belongs exactly to one cluster. In soft clustering data element can belong to more than one cluster.

FUZZY CLUSTERING MEAN (FCM)

The most widely used fuzzy clustering algorithm is fuzzy clustering mean (FCM). It is also known as soft clustering the element can belong to more than one cluster, and related with each element is a set of membership levels. These specify the strength of the group between the element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign

element to one or more clusters. Therefore it can be well thought-out that the difficulty of change detection can be viewed as a clustering problem. The clustering algorithm is unrestricted by the statistical model for changed and unchanged class distributions, which provides it broad scenario in change detection of SAR images. FCM algorithm which retains more information about the original image however it is very sensitive to noise therefore it does not consider any spatial context information.

ALGORITHM

STEP 1) Initializes the matrix

STEP 2) Assume random centres

STEP 3) Start iterative process and calculate the new centres.

STEP 4) Compare the new centres with the old centres if it satisfies the stopping condition end there and assign the centres and cluster data's are categorized.

FUZZY LOCAL INFORMATION CLUSTERING MEAN (FLICM)

The features of FLICM is the use of a fuzzy local match measure, which is intended at guaranteeing noise insensitive and it retain the image detail. To improve the clustering performance of FLICM fuzzy factor G_{ki} is introduced. Both noise pixels and no noisy pixel falls in local window, will unite as like value and thereby balance the membership value of the pixels that are located in the window. It does not use any artificial parameter and being useful straight to the original image.

$$G_{ki} = \sum_{j \in N_i} 1/d_{ij} + (1 - u_{ki})^n \|x_i - v_k\| \quad (8)$$

Where j th pixel denotes the neighboring pixel falling around the window of i th pixel, i th pixel is the center of the local window and d_{ij} is the spatial euclidean distance between i and j pixels. v_k denotes the structure of the centre cluster k and u_{ki} represents the gray value of the fuzzy membership with esteem to k th cluster. Without using any artificial parameter it is insensitive to noise and preserve the image details. The influence of pixel within the local window in G_{ki} is exerted flexibly by using their euclidean distance from the centre pixel.

ALGORITHM

STEP 1) Set the number of cluster prototype c , fuzzification parameter n and the stopping condition ϵ .

STEP 2) Initialize the fuzzy partition matrix randomly.

STEP 3) Set the loop counter $b=0$.

STEP 4) Compute the cluster prototypes using

$$U_{ki} = \frac{1}{\sum_{j=1}^c \left[\frac{\|x_i - v_k\|^2 + G_{ki}}{\|x_i - v_j\|^2 + G_{ji}} \right]^{1/(m-1)}} \quad (9)$$

STEP 5) calculate the fuzzy partition matrix

$$V_k = \frac{\sum_{i=1}^N u_{ki}^m x_i}{\sum_{i=1}^N u_{ki}^m} \quad (10)$$

STEP 6) $\max \{u^{(b)} - u^{(b+1)}\} < \epsilon$ then stop; if not set $b=b+1$, and repeat from step 4.

REFORMULATED FUZZY LOCAL INFORMATION CLUSTERING MEAN (RFLICM)

RFLICM is used to suppress the effect of speckle noise. Local coefficient of variation is added instead of spatial distance. The reformulated factor considers the local coefficient of variation and the gray level of neighbouring pixels to balance the membership value of the central pixel. Weighting added of the neighbouring pixel will be increased to restrain the background information, if there is dissimilar variation between the results of the local coefficient of variation that are obtained by the central pixel and neighbouring pixel.

The fuzzy factor of RFLICM can be defined as

$$G_{ki} = \sum_{j \in N_i} \epsilon N_i [1/2 + \min((C_{ju}/C_u)^2, (C_u/C_{ju})^2)] \quad (11)$$

$$C_u = \text{var}(x) / (\bar{x})^2 \quad (12)$$

Where $\text{var}(x)$ and \bar{x} are the mean and intensity variance of the image. v_k is sample value of k th cluster, C_{ju} is the neighbouring pixels of local coefficient of variation, C_{ju} is neighbouring pixel of local coefficient of variation, C_u is the central pixel of local coefficient of variation.

ALGORITHM

STEP 1) Set the cluster prototypes c , fuzzification parameter m and the stopping condition ϵ .

STEP 2) Initialize fuzzy partition matrix randomly.

STEP 3) Set the loop counter $b=0$

STEP 4) Determine the cluster prototype using (9)

STEP 5) calculate the partition matrix using (10)

STEP 6) $\max \{U^{(b)} - U^{(b+1)}\} < \epsilon$ then stop; otherwise set $b=b+1$, and go to step(4).

MARKOV RANDOM FIELD (MRF)

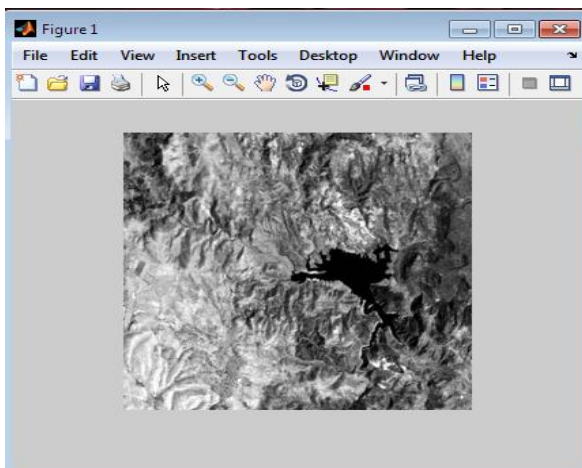
Markov random field reduces the amount of speckle noise by modifying the membership of each pixel by the relationship of neighborhood pixels. The term is dependent on different situations, and is established by using the least square method. MRF is computationally simple and which leads to less consumption time compared to other FCM algorithms.

MRF provides a basis for modeling information about the mutual influences among image pixels. In MRF energy function which directly characterizes the way to utilize spatial context. Considering the severe speckle noise in SAR images, the relationship among pixels is more complex than in other kind of image. Such complexity appears as two aspects: they are homogeneous regions in DI and heterogeneous regions in DI. Thus, the energy function of MRF instead of modifying the membership value, it modifies the objective function. Thus, MRFFCM modifies the membership of each pixel according to the MRF-based spatial context. The spatial context contains the essential energy through the use of the neighborhood system. The information provided by the neighborhood pixel serves as the spatial context.

III. SIMULATION RESULTS

SAR IMAGE

The fig(3) is taken as the first input image acquired in September 1995 before flooding at Sardinia, and the fig(4) is taken as the second input image which is acquired in August 1996 after flooding at Sardinia for change detection process.



Fig(3) SAR Image 1

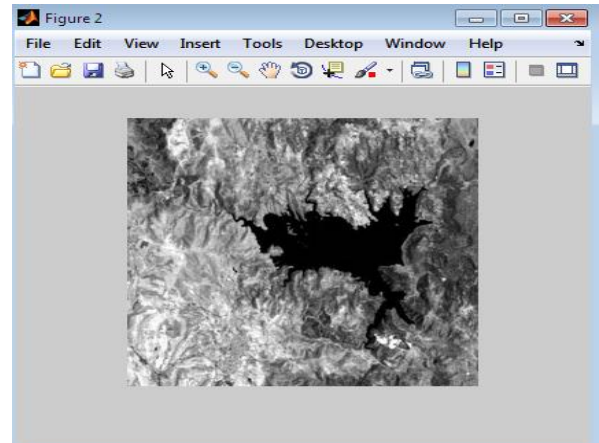
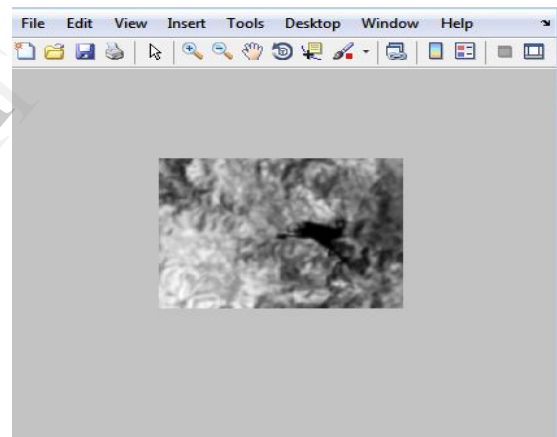


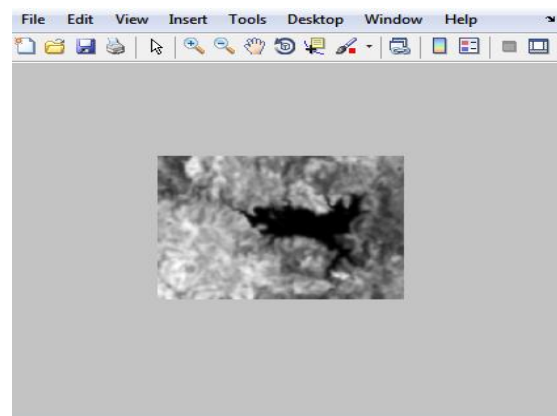
fig (4) SAR image 2

SRAD IMAGE

The fig(5) and fig(6) are speckle-reducing anisotropic diffusion images which reduce the amount of speckle noise presented in the input image.



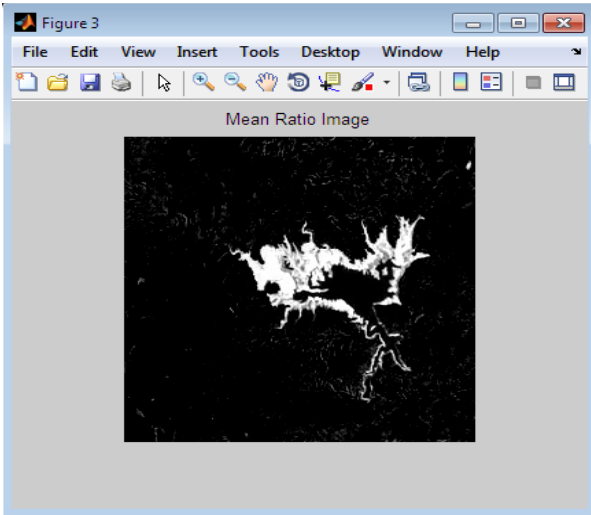
Fig(5) SRAD Image 1



fig(6) SRAD Image 2

MEAN RATIO IMAGE

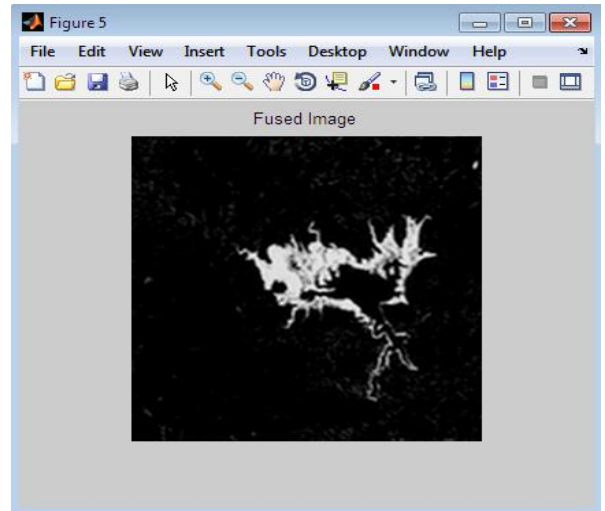
Mean ratio image fig(7) is obtained by mean ratio operator. It represents the local mean value of the input images.



Fig(7) Mean ratio image

FUSED IMAGE

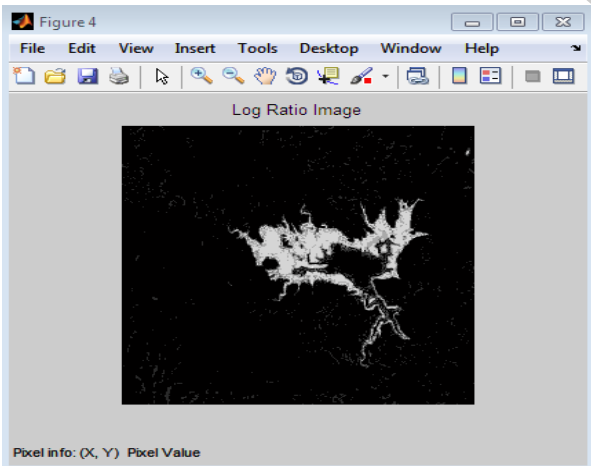
Fused image fig(9) generates the difference using the wavelet fusion based on mean ratio image and log ratio image.



Fig(9) fused image

LOG RATIO IMAGE

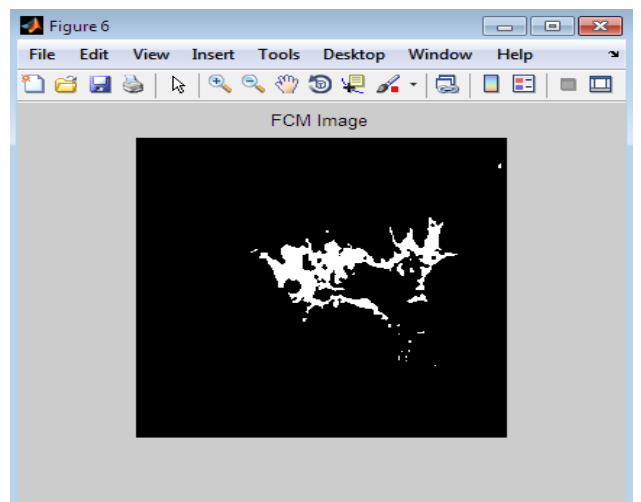
Log ratio image fig(8) is obtained by log operator . It represents the logarithmic value of the input images.



Fig(8) Log ratio image

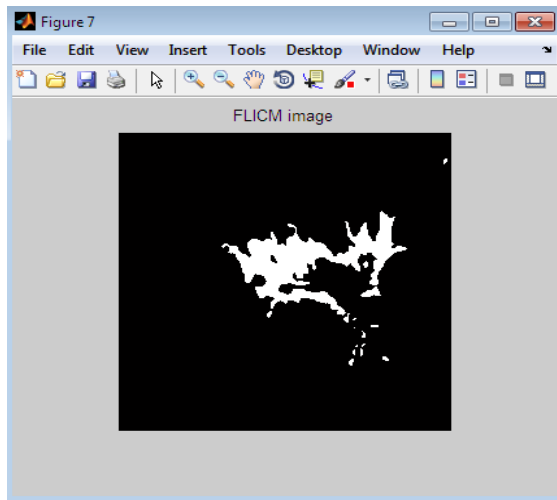
FCM IMAGE

Fig (10) is the automatic analysis of fused image using fuzzy clustering algorithm. This represents the changed and unchanged region.



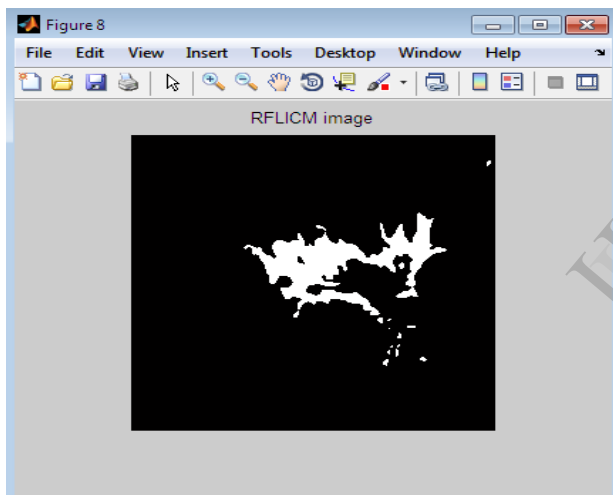
Fig(10) FCM Image

FLICM IMAGE



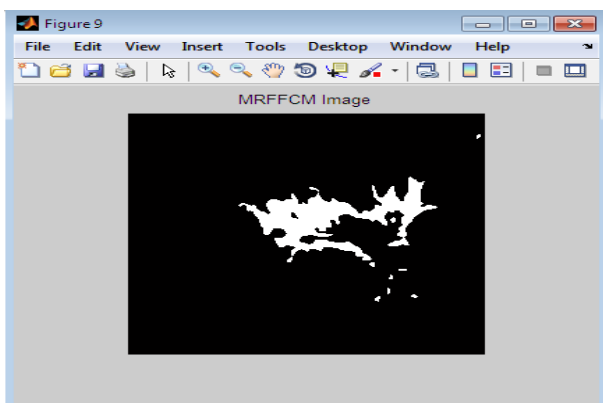
Fig(11) FLICM Image

RFLICM IMAGE



Fig(12)RFLICM Image

MRFFCM IMAGE



Fig(13) MRFFCM Image

IV. CONCLUSION

In this research paper we proposed the changed and unchanged detection of the images using four different algorithms. Among those MRF algorithm efficiently reduces the speckle noise.computation time and complexity are also reduced by the proposed method.

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