International Journal of Advance Research in Science and Engineering
Vol. No.4, Issue No. 12, December 2015
www.ijarse.com
IJARSE
ISSN 2319 - 8354

MOVING OBJECT DETECTION USING IMAGE FUSION AND FUZZY CLUSTRING

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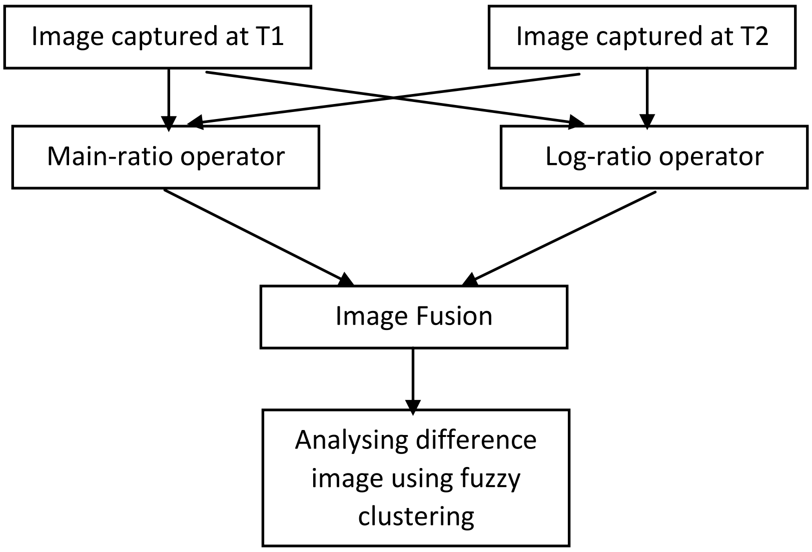
ABSTRACT

Radar is the word which plays a major role when coming to the defence system in fields like military etc. It plays major role to detect the distance between the object and current location and also need to know that object is moving close or moving away. In our proposed system we are using Synthetic Aperture Reader which means detecting the object size and distance using the image processing. Two images of different time line are considered and two images are processed using log-ration, mean-ration images are combined into one image using image fusion techniques. To restrain the background information of an image we are going to fuse the image separately with the low frequency components, high frequency components differently using the Discrete Wavelet Transforms. By using the DWT instead of using the directly fusing the image we may loss the data at the image noise pixels, since we separated the images according to the frequencies we are able to get exact data. In our proposed system reformulated Fuzzy clustering in C-means clustering algorithm is proposed to detect the back ground and fore ground of an image which is divided individually after the DWT. Our proposed system shown improved results when compared to the traditional Synthetic Aperture Radar.

I. INTRODUCTION

In digital images we are using everyday life all the pixels in the images are not the important pixels, some pixels are noisy pixels. We don't notice in image of noise, and the original pixels and the noisy pixels are separated using the low pass filter and high pass filter. By using the Discrete Wavelet Transform we can separate the important and noisy pixels by applying the Low-pass filter and High-pass filter separately. After applying the DWT to an image we directly gets the four level images which are known as Low-Low image, Low-High image, High-Low image, High-High image. Out of all the four images. Most of the original pixels stays in the Low-Low image, and the original pixels in the image reduces from Low-Low to the High-High, most of the noise pixels stays in the high-high filter. The original and noise pixels are divided on the basis of the intensity too. We get the accurate output by dividing the high pass and low pass filters, instead of applying the fusion to the entire image directly. The main application of the image fusion is to get the appropriate image output by having the two images differently. There are mainly two types of the image fusion techniques which mean ratio based and the log-ratio based. Both of the fusion techniques have different application and we are using both log-ratio and mean-ratio individually to have a batter comparison. Then the image fusion is applied such that we can get the noise and the important pixels. Even though we can exclude the noise pixels while subtracting the image with other image the effect of noise impact on the result image. Because when we subtract the noise pixel may subtracted from the original pixel instead of subtraction from the noise pixel. To avoid such kind of errors are dividing the images from the low frequency to low frequency and high frequency to high frequency separately. Once we successfully subtracted or detected the back ground of the image we can detect the object is moving close or moving away by checking the size or the pixels in the object. The obtained fused imaged mostly contains the subtracted pixels means the high pixels represent the differences and low pixels represents the unchanged pixels, which are also known as back ground.



The above block diagram describes the log-mean ratio operator working, section of our proposed system which is further processed according to the DWT wavelet calculation which are given below

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

$$X_l = \left|log\frac{X_2}{X_1}\right| = |logX_2 - logX_1|$$

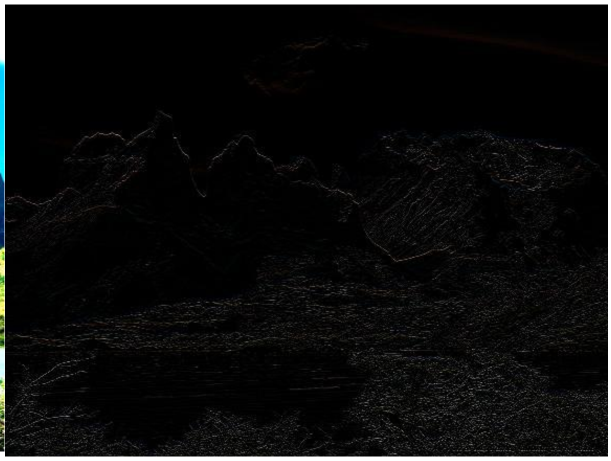
Here μ_1 *and* μ_2 are known as local mean of multi temporal SAR images of X_1 and X_2.

In Discrete Wavelet Transform there are mainly three types of transformations which are

- Harr
- Daubechies wavelets
- Dual-tree Complex Wavelet transforms

Harr transform is widely used in the many fields like pixel separation, here is how the harr transform separates the image by applying the low pass and high pass filters. Here is the considered original image and the extracted low pass and high pass filters.

Considered original image



(1) Low pass low pass image **(2) Low pass High pass image**

(3)High pass low pass image **(4) Low pass Low pass image**

The two images X_l and X_m images are processed according to below block diagram.

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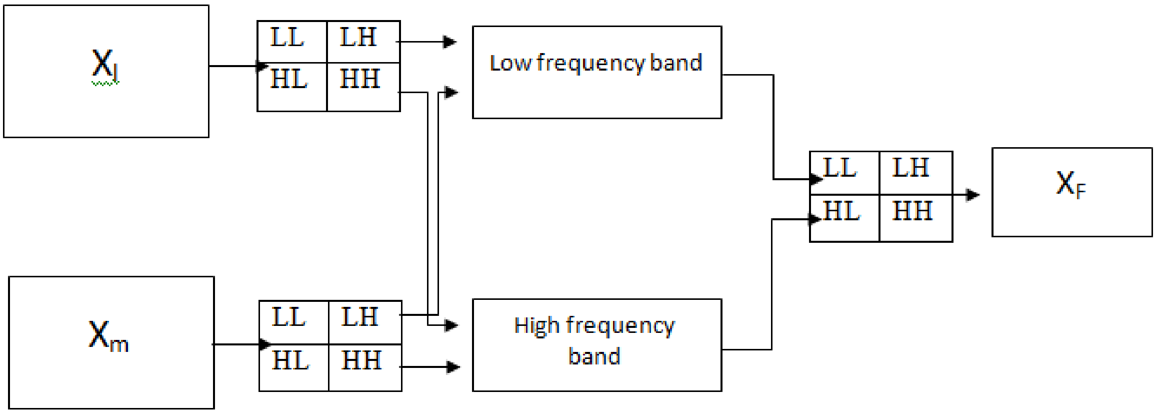
ISSN 2319 - 8354



In the above block diagram it is clearly mentioned that resultant image is obtained by differentiating the two different band images separately. Two fusion regulations are applied, those are

- Selecting average value with respective of coefficients of low frequency band
- Selecting minimum area energy coefficient of high frequency band.

These rules are represented as fallows

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

$$D_{\varepsilon}^{F}(i,j) = \begin{cases} D_{\varepsilon}^{m}(i,j), & E_{\varepsilon}^{m}(i,j) < E_{\varepsilon}^{l}(i,j) \\ D_{\varepsilon}^{l}(i,j), & E_{\varepsilon}^{l}(i,j) \geq E_{\varepsilon}^{l}(i,j) \end{cases}$$

Where l and m represent mean-ratio image and log-ratio images.

F denotes new fused image.

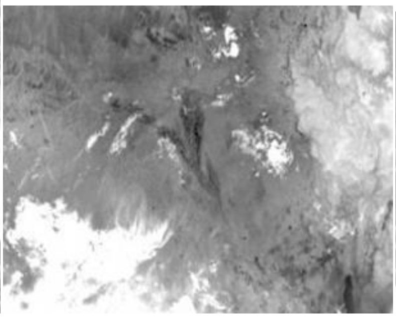
D_{LL} stands as low-frequency coefficients.

$D\varepsilon(i,j), (\varepsilon = LH, HL, HH)$shows total three different high-frequency coefficients at (i,j).

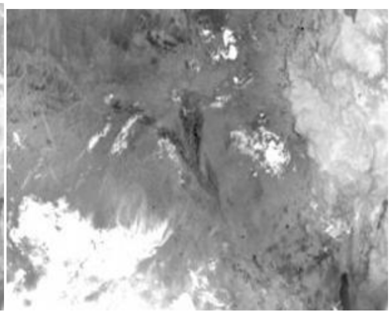
$$E_{\varepsilon}(i,j) = \sum_{k \epsilon N_{i,j}} [D_{\varepsilon}(k)]^2$$

II. RESULTS

Original SAR image at t1



Original SAR image at t2



Original SAR image one grey

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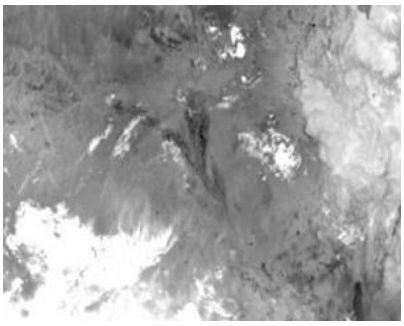
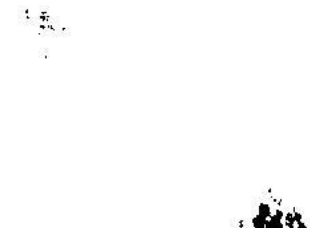
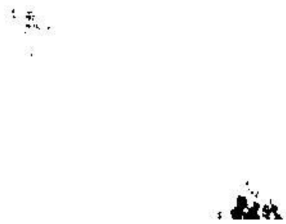
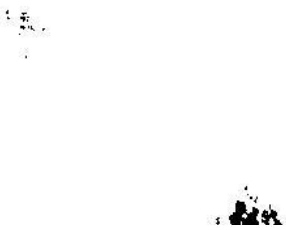
ISSN 2319 - 8354







Original SAR image two grey   Mean ratio operator   Log ratio operator



DWT based fused image   Ground truth image   FLICM image

Resultant image

Percent correct classification of LOG RATIO =1

KAPPA for RFLICM UNWEIGHTED COHEN'S KAPPA

Observed agreement (po) = 0.9901&Random agreement (pe) = 0.9685

Agreement due to true concordance (po-pe) = 0.0215, Residual not random agreement (1-pe) = 0.0315

Cohen's kappa = 0.6842, kappa error = 0.0117, kappa C.I. (alpha = 0.0500) = 0.6613   0.7070

Maximum possible kappa, given the observed marginal frequencies = 0.6842

k observed as proportion of maximum possible = 1.0000

Substantial agreementVariance = 0.0000   z (k/sqrt(var)) = 162.1237   p = 0.0000

Reject null hypotesis: observed agreement is not accidental

KAPPA for FLICM UNWEIGHTED COHEN'S KAPPA

Observed agreement (po) = 0.0101, Random agreement (pe) = 0.0123,

Agreement due to true concordance (po-pe) = -0.0021, Residual not random agreement (1-pe) = 0.9877

Cohen's kappa = -0.0021, kappa error = 0.0004, kappa C.I. (alpha = 0.0500) = -0.0029   -0.0014

Maximum possible kappa, given the observed marginal frequencies = 0.0000 k observed as proportion of maximum possible = -74.4879,

Poor agreementVariance = 0.0001 z (k/sqrt(var)) = -0.2885 p = 0.7730

Accept null hypotesis: observed agreement is accidental

III. CONCLUSION

In above picture we considered two images which is captured from the webcam and calculated the difference in the image using log-mean and DWT methods to acquire accurate difference in two time frame images and detected the moving object successfully.

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