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Image Fusion on Ratio Images for Change Detection in SAR Images Using DWT and PCA

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ABSTRACT
This paper presents image fusion techniques on ratio images for change detection in synthetic aperture radar (SAR) images. In this we are implementing wavelet fusion and PCA fusion techniques. The proposed approaches are applied to generate the fused image by using complementary information from mean-ratio and log-ratio images. To restrain the background (unchanged areas) information and enhance the information of changed regions in the fused image, fusion rules based on weight averaging and minimum standard deviation are chosen to fuse the wavelet coefficients for low- and high-frequency bands, respectively. PCA fusion algorithm is applied on ratio images to get good results in change detection. Experiments on real SAR images confirm that the PCA fusion does better than the mean-ratio, log-ratio and wavelet fusion.

Keywords – log-ratio image, mean-ratio image, PCA fusion, synthetic aperture radar (SAR) image, wavelet fusion.

I. INTRODUCTION

Image Fusion is a process of combining the relevant information from a set of images into a single image, the resultant fused image will be more informative than any of the input images. Detecting regions of changes in geographical area at different times is of widespread interest due to large number of applications in several disciplines [1]. SAR data can guarantee operational systems in the presence of unfavorable atmospheric circumstances and the absence of solar illuminations. In view of these advantages, SAR images should be valuable sources of information in change detection [2]. The ratio operator is the most widely used technique to generate difference image [2], [3]. The logarithm of ratio image since it can transform the multiplicative speckle noise into an additive noise component. A ratio mean detector, which is robust to speckle noise [3]. Both methods have yielded effective results for change detection in SAR images, but still have some disadvantages. The log ratio operator is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high-intensity. Hence, the information of changed regions obtained by the log-ratio image may not be able to reflect the real changed trends in the maximum extent. The mean-ratio detector may fail to detect changes since it assumes that a change in the scene will appear as a modification of the local mean value of the image [3]. In order to address the problem previously mentioned, this paper presents fusion algorithms to generate fused image based on discrete wavelet transform (DWT) and principal component analysis (PCA) for better change detection.

II. PROPOSED METHODS

Consider the two co-registered intensity SAR images $\mathrm{A1}$ and $\mathrm{A2}$ acquired over the same geographical area at two different time intervals.

2.1 Mean Ratio and Log Ratio operators

The mean-ratio operator should be applied to generate the mean-ratio image. It can be defined as follows:

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

Where, $\mu_1(i,j)$ and $\mu_2(i,j)$ represent the local mean values of the pixels in a neighborhood of point (i,j) in $\mathrm{A1}$ and $\mathrm{A2}$, respectively. Above equation shows that the mean-ratio operator produces difference image by using the local mean information of each pair of co-located pixels. Similarly the absolute valued log-ratio operator is applied in our paper to indicate the change regions. It can be defined as:

$$\mathrm{A}_l=\left|\log\left(\mathrm{A}_2/\mathrm{A}_1\right)\right|=\left|\log \mathrm{A}_2-\log \mathrm{A}_1\right| \quad (2)$$

Where, log stands for natural logarithm [4].

2.2 Wavelet Fusion

Image fusion is the technique that combines information from multiple images of the same scene taken over different time intervals .The result of image fusion is a new image that shows the most desirable information and characteristics of each input image. Image fusion techniques mainly take place at the pixel level of the source images. Multi scale transform, such as the DWT has been extensively used for the pixel-level image fusion [5]. DWT isolates frequencies in both space and time, allowing detail information to be easily extracted from images. Its simplicity and its ability to preserve image details with point discontinuities make the fusion scheme based on DWT suitable for the change detection task [1]. Figure (1) shows the main steps of the image fusion scheme based on wavelet transform can be described as follows:

1) Compute the DWT of each of the two source images and obtain the multi-resolution decomposition of each source image.

2) Fuse corresponding coefficients of approximate and detail sub-band of the decomposed source images using the developed fusion rule in the wavelet transform domain. The wavelet coefficients are fused using different fusion rules for low-frequency and high-frequency bands.

3) The fused image is obtained by applying the inverse DWT.

Here, two main fusion rules are applied, i.e., the rule of selecting the weight averaging for the low-frequency band and the rule of selecting the minimum standard deviation wavelet coefficient for the high-frequency band. Fusion rules can be described as follows:

$$D_{LL}^{F} = \alpha D_{LL}^{l} + \beta D_{LL}^{m} \tag{3}$$

$$\alpha = \min\left(\left|D_{LL}^{l}\right|, \left|\overline{D_{LL}}\right|\right) \Big/ \max\left(\left|D_{LL}^{l}\right|, \left|\overline{D_{LL}}\right|\right) \tag{4}$$

$$\beta = \left(1 - \min\left(\left|D_{LL}^{l}\right|, \left|\overline{D_{LL}}\right|\right)\right) \Big/ \max\left(\left|D_{LL}^{l}\right|, \left|\overline{D_{LL}}\right|\right) \tag{5}$$

$$D_{e}^{F}(i,j) = \begin{cases} D_{e}^{m}(i,j), \sigma_{e}^{m}(i,j) < \sigma_{e}^{l}(i,j) \\ D_{e}^{l}(i,j), \sigma_{e}^{m}(i,j) \geq \sigma_{e}^{l}(i,j) \end{cases} \tag{6}$$

Where, *m* and *l* represent the mean-ratio and log-ratio images respectively. *F* denotes the new fused image. D_{LL} Stands for low-frequency coefficients, and $\overline{D_{LL}}$ is the mean value of the two source images low-frequency coefficient. $D_e(i,j)$, where, $(e \in \{LH, HL, HH\})$ represents three high-frequency coefficients at point (i,j)in the corresponding sub images. The low-frequency sub-band represents the information of changed regions of two source ratio images. In order to reflect the real changed trend and reduce the effect of noise, the method based on weight averaging is selected to fuse the wavelet coefficients for low-frequency sub-band.

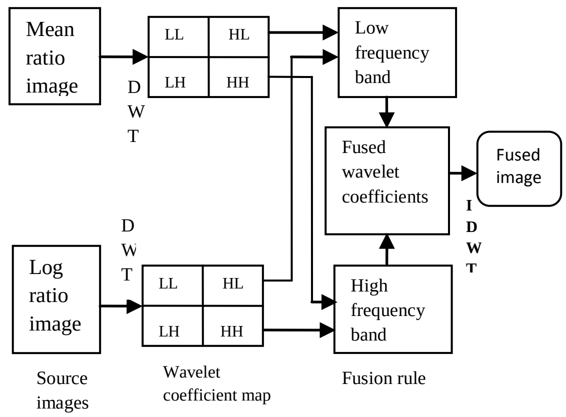

Figure 1: Process of image fusion based on the DWT

The weights for log-ratio and mean-ratio images, namely α and β, are used to control the effect of each source image's wavelet coefficient. Parameter β will help enhance the information of changed regions. The high-frequency sub bands denote the information about edges and lines. The standard deviation indicates the deviation extent between the wavelet coefficient and its local mean value. Hence, this rule can merge the homogeneous regions of high-frequency portion from mean-ratio and log-ratio images.

2.3 PCA Fusion

Principal component analysis (PCA) is a mathematical procedure that transforms a number of correlated variables into a smaller number of uncorrelated variables called principal components. In these variables the first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. A common way to find the principal components of a data set is by calculating the eigenvectors of the data covariance matrix. The corresponding Eigen values give an indication of the amount of information that the respective principal components represent. Principal components corresponding to large Eigen values represent a large amount of information in the data set and thus tell us much about the relations between the data points. Principal component analysis is used to enhance the features in the original images and also reduce noise level. PCA helps to reduce redundant information and highlight the components with biggest influence so as to increase the signal-to-noise ratio.

Let $x_1, x_2 ..... x_n$ are values of first pixel in each of the n' images then 'n' elements can be expressed as a column vector of x.

Mean vector of population is:

$$m_x = E[x] \tag{7}$$

The covariance matrix of vector population is described as follows:

$$C_x = E\{(x-m_x)(x-m_x)^T\} \quad (8)$$

For a sample of N vectors from a random population, the mean vector and covariance matrix can be given by the following expressions:

$$m_x = \left(\frac{1}{N}\right)\sum_{K=1}^{N} x_k \quad (9)$$

Thus covariance matrix can be given by the expression:

$$C_x = \left(\frac{1}{N}\right)\sum_{K=1}^{N} x_k x_k^T - m_x m_x^T \quad (10)$$

Since C_x is real and symmetric.

Let e_i and λ_i be eigenvectors and corresponding eigenvalues of C_x where i = 1, 2, ---, N. A is a matrix whose rows are eigenvectors of covariance matrix C_x. The first row of A is eigenvectors corresponding to the largest eigenvalue, and last row correspond its smallest eigenvalue [6]. If A as transformation matrix to map the x into Y, then Y is given by:

$$Y = A(x - m_x) \quad (11)$$

Above expression of 'Y 'is called Principal Component Transform. The figure (2) shows the PCA fusion process and it is described as follows [7]:

1) Generate the column vectors, from the input image matrices.
2) Calculate the covariance matrix of the two column vectors formed in step 1.
3) Calculate the Eigen values and the Eigen vectors of the covariance matrix.

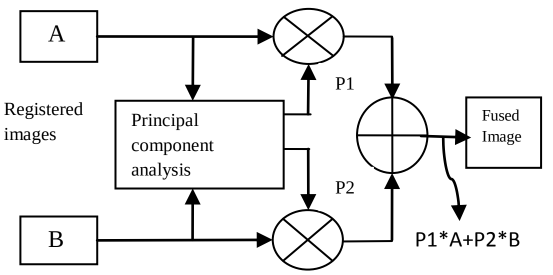

Figure 2: Block diagram of PCA fusion process.

4) Normalize the column vector corresponding to the larger Eigen value by dividing each element with mean of the Eigen vector.
5) The values of the normalized Eigen vector act as the weight values which are respectively multiplied with each pixel of the input images.
6) Sum of the two scaled matrices calculated in 5 will be the fused image matrix.

III. EVALUATION OF PARAMETERS

3.1 Entropy

Entropy is defined as amount of information contained in a signal. The entropy of the image can be calculated as follows:

$$H(x) = -\sum_{i=1}^{G} P_i \log_2(P_i) \quad (12)$$

Entropy can directly reflect the average information content of an image. If entropy of fused image is higher than parent image then it indicates that the fused image contains more information.

3.2 Root mean square error (RMSE)

The root mean square error (RMSE) is defined as follows:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(R(m,n) - F(m,n))^2} \quad (13)$$

Where, R (m,n) and F(m,n) are reference and fused images, respectively, and M and N are image dimensions.

3.3 Peak signal to noise ratio

Peak signal-to-noise ratio is used as a quality measurement between the original and a reconstructed image. The higher the PSNR, the better is the quality of the reconstructed image. First we have to compute the mean squared error (MSE) and then compute the PSNR using the following equations:

$$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(R(m,n) - F(m,n))^2 \quad (14)$$

$$PSNR = 10\log_{10}\left(\frac{MAX_R^2}{MSE}\right) \quad (15)$$

Where M and N are image dimensions and MAX_R is the maximum possible pixel value of the image. Generally, when samples are represented using linear PCM with *B* bits per sample, MAX_R is 2^B-1.

IV. DATASET DESCRIPTION AND EXPERIMENTAL RESULTS

The data set represents a region surrounding the city of Sicily, Italy. Detailed descriptions of this dataset and the experimental activity are provided in the following.

4.1 Sicily Dataset

The dataset used in the experiment is made up of two SAR images acquired by the European Remote Sensing 2 satellite SAR sensor. From the two images of the city of Sicily acquired on July 14 and 26, 2011 are shown in (Fig. 3) and (Fig. 4), it is possible to analyze which parts of the area were affected by the flooding that occurred just before the first acquisition date. In this experiment, we analyzed the changed regions which are affected by the floods. For this we are performing two ratio operators to detect the changed regions in the SAR images. The log-ratio image generated from the original images is shown in (Fig. 5), from this figure we can observe the changed regions of the SAR images. The mean-ratio image generated from the original images is shown in (Fig. 6), from this figure we can observe the changed regions of the SAR images. These two operators have given the changed regions with some differences, to get more information of the changed areas we have to fuse the log-ratio and mean-ratio operators. Here, two fusion algorithms are performed to produce the change detection map; those are Discrete Wavelet Transform and Principal Component Analysis methods. DWT fused image is shown in (Fig. 7) and PCA fused image is shown in (Fig. 8). The above mentioned fused images are used to highlight all the portions of the changed areas in the best possible way. These two images contain the more information of changed regions than the images which are produced by the log-ratio and mean-ratio operators. Table.1 summarizes the quantitative results obtained by comparing the change-detection maps yielded applying the proposed techniques and classical change detection algorithms. The peak signal to noise ratio and entropy of the change detection maps are higher for PCA fusion technique and the root mean square error is low for PCA fusion technique compared with Discrete Wavelet Transform, log-ratio and mean-ratio operators. In addition, by a visual analysis of (Fig. 8), it is clear that the change-detection map obtained with the PCA technique is more informative than DWT technique, log-ratio and mean-ratio operators.

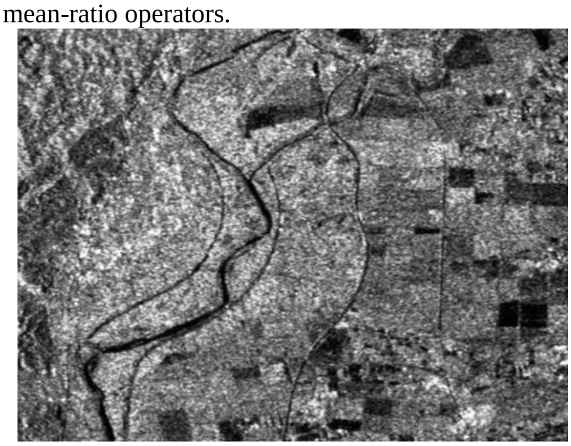

Figure 3.SAR image acquired on July 14, 2011

Figure 4.SAR image acquired on July 26, 2011

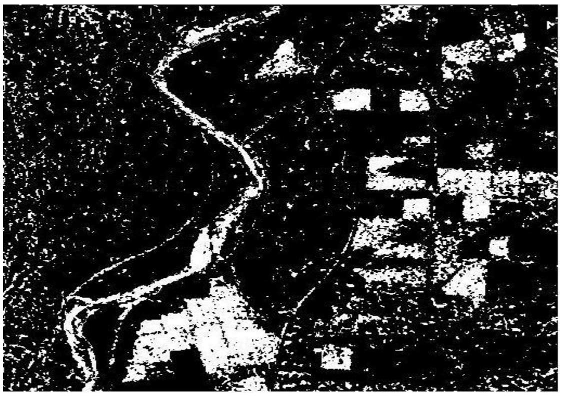

Figure 5. change detection result from log-ratio operator

Figure 6.change detection result from mean-ratio operator

Table 1.Evaluated parameters

METHOD	Log ratio	Mean ratio	Wavelet fusion	PCA fusion
PSNR	67.00	69.04	71.76	74.98
RMSE	0.22	0.18	0.13	0.09
ENTROPY	0.63	0.36	1.31	2.37

Figure 7.change detection result from DWT fusion

Figure 8.change detection result from PCA fusion

V. CONCLUSION

In this paper we proposed two fusion methods based on wavelet transform and principal component analysis to generate fused image for change detection in SAR images. In these methods, complementary information from mean-ratio and log-ratio images has been utilized to fuse a new fused image. The experimental results indicated that the peak signal to noise ratio, root mean square error and entropy values of PCA fused image are better than the mean-ratio operator, the log-ratio operator, and the wavelet fusion in most cases.

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