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Novel Fusion Rules for Discrete Wavelet Transform based Image Fusion

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Abstract

Objective: The accuracy and reduction in speckle noise is an issue of major concern in change detection methods. In this paper, new fusion rules for Discrete Wavelet Transform (DWT) based image change detection have been proposed. **Method:** Multi-temporal images have been applied to Log Ratio and Mean Ratio operators to generate the source images. Both the source images are decomposed into wavelet coefficients through DWT. The fused image is obtained by applying the proposed fusion rules on the decomposed wavelet coefficients. The fusion rules for low frequency sub-band is based on addition of the average and maximum value of the wavelet coefficients while the fusion rule for high frequency sub-band is based on the neighborhood mean differencing of the coefficients. **Findings:** The difference image is generated by applying inverse wavelet transform on the fused coefficient map. The changed and unchanged areas have been classified by Fuzzy C Means (FCM) clustering. The results have been compared based upon parameters like Overall Error (OE), Percentage Correct Classification (PCC) and Kappa Coefficient (KC). The qualitative and quantitative results show that the proposed method offers least overall error. The accuracy and Kappa value of proposed method are also better than its preexistences. **Application:** The method has applications in remote sensing, medical diagnosis and disaster management.

Keywords: Change Detection, Discrete Wavelet Transform, Fuzzy Clustering, Image Fusion, Log Ratio, Mean Ratio

1. Introduction

Change detection in images involves comparing multi-temporal set of images of a scene captured at different times to generate a difference image[1]. Change detection has wide scope in many applications including remote sensing, medical diagnosis and disaster managements[2-5]. The main issue of concern in change detection is the accuracy of the algorithm to detect the changed and unchanged pixels with minimum speckle noise[6]. The most popular change detection operators are differencing and rationing[7]. In image differencing, the corresponding pixel in one image is subtracted from the second. In image rationing, the corresponding values of pixels in multi-temporal images are divided to get the output image[8]. However, the output of different change detectors can be combined to obtain enhanced image which contain features *of* both the images[9]. Many image fusion methods have been proposed in literature including discrete wavelet transform, Stationary wavelet transform and Nonsubsampled contourlet transform[10-12]. In wavelet based image fusion, each of the source images is decomposed into four images to obtain the wavelet coefficient map. Each of the wavelet coefficient map contain one low frequency sub-band representing the approximate portion of the image and three high frequency sub-bands representing the horizontal, diagonal and vertical components of the image. Then fusion rules are applied separately on both the side-bands.

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In the last step, inverse wavelet transform is applied on the fused coefficient to get a fused image. The fused image obtained from image fusion presents the features of both the source images which improve the quality of the output image. Defining fusion rule is the most important step in image fusion. Many fusion rules have been proposed in the literature like rules based on minimum local area energy coefficient[10], minimum standard deviation[11] and minimum value of the coefficients[12].The main issue in the selection of fusion rules is the suppression of background information and the enhancement in the changed regions of the image. Finally, the changed and unchanged areas are classified using clustering method. Many clustering methods have been proposed in the literature like fuzzy c means clustering[13,14], k means clustering[15] and non subsampled contourlet transform based clustering[16-18].

As mentioned in the literature, the quality of the fused image depends upon the fusion rules employed in image fusion. In order to address the issue, this paper proposes a change detector with new fusion rules based on neighborhood mean differencing of the wavelet coefficients of both the images. The source images obtained from mean ratio and log ratio has been fused by discrete wavelet transform through proposed fusion rules. The changed and unchanged has been classified using fuzzy c means clustering.

This paper is organized into four sections. The next section introduces the methodology used for change detection. The experimental results has been presented and discussed in the third section. The last section presents the conclusion.

2. Methodology

Consider two co-registered images $I_1 = \{I_1(i, j), 1 < i < R, 1 < j < C\}$ and $I_2 = \{I_2(i, j), 1 < i < R, 1 < j < C\}$ of size R×C, i.e., of a scene taken at different times t_1 and t_2 respectively. The methodology involves the three main steps. In the first step, Log ratio and Mean ratio operators are applied on two multi-temporal images respectively to generate two source images. In the second steps, the two source images are fused together by using proposed fusion rules in DWT based image fusion method. In the last step, the fused image is classified into changed and unchanged areas by fuzzy c means clustering.

In Log Ratio operator, natural logarithms of the ratio of pixels in the images are calculated as given in Equation 1. Applying Log operator on an image enhances the low frequency components and suppresses the high frequency features in the output image.

$$I_l(x, y) = \frac{\log(I1(x, y))}{I2(x, y)} \quad (1)$$

In case of Mean Ratio operator, the local mean of the pixel in one image is divided with the local mean of the corresponding pixel in the second image. The output of mean ratio is robust to speckle noise.

$$I_m(x, y) = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right) \quad (2)$$

Where $\mu_1 and \mu_2$ in Equation 2 represents the local mean value of the pixel in the neighborhood of first and second image respectively [9].

In DWT, the detail information from the images can be easily extracted because the frequencies are isolated in time as well as in space. DWT is very simple to implement and it preserves the details in the images which makes it more suitable for change detection application is shown in Figure 1.

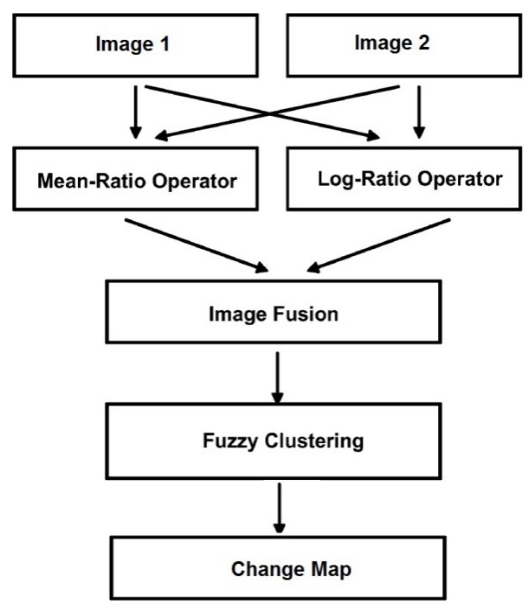


Figure 1. Methodology for Change Detection.

In image fusion based on wavelet transform, discrete wavelet transform of each of the source images is computed which gives the wavelet coefficient of both the images. The fusion rules are then applied in order to fuse the corresponding coefficients of the decomposed source images. Selection of fusion rules is the most important step in image fusion. The proposed algorithm focuses on defining the fusion rule so as to suppress the background information and enhance the information of the changed region in the source images. The rules are defined so as to maximize the edge features in the fused image and suppress the background information as maximum as possible. Different fusion rules are applied on the coefficients of low frequency and high sub-band because both the sub-bands contain the difference features. However, two fusion rules are proposed here. The fusion rule for low frequency sub-band combines the maximum value with the average of the mean ratio and log ratio coefficient. The rule for high frequency sub-band calculates the neighborhood mean of the log ratio and mean ratio image. Then the fused coefficients are obtained by differencing the minimum value from the maximum value of the coefficients.

Fusion Rule for Low frequency sub-band

$$I_{LL}^{f} = \alpha \times \max\left(I_{LL}^{l}, I_{LL}^{m}\right) + (1+\alpha) \times \frac{\left(I_{LL}^{l} + I_{LL}^{m}\right)}{2} \quad (3)$$

Fusion Rule for high frequency sub-band

$$I_{\varepsilon}^{f} = \max(\mu_{\varepsilon}^{l}, \mu_{\varepsilon}^{m}) - \min(\mu_{\varepsilon}^{l}, \mu_{\varepsilon}^{m}) \quad (4)$$

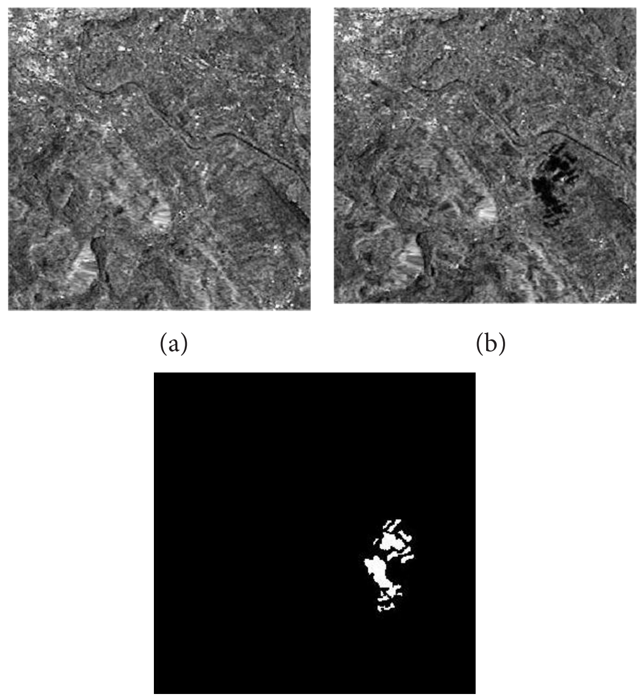
Here α in equation 3 is a positive number. m, l and f represents the mean ratio, log ratio and fused images respectively. I_{LL} represents the coefficients of low frequency sub-band while Ie(e= HL, LH and HH) represents the coefficients of high frequency sub-band. μ^{l} and μ^{m} Represents the local mean of the coefficients of the neighborhood window in the high frequency sub-band for log ratio and mean ratio respectively. In the next step, inverse wavelet transform is applied on the fused wavelet coefficients map to get the fused image. A window size of 3×3 has been selected in the algorithm. The proposed rules for low frequency sub-band enhances the edge features of changed regions of the source image while in high frequency sub-band, the fusion rule is selected in such a way to suppress the background information.

3. Experimental Results

In this section, the performance of the proposed method will be evaluated on the Bern dataset. The performance will be compared with the state of the art methods including DWT based image fusion (DWT-FCM) in which minimum local area energy coefficient based fusion rule has been used [10]and context independent variable behavior (DWT-CIVB) operator in which minimum standard deviation based fusion rule has been used[11]. In the proposed method, the value of α has been taken as 0.3.

3.1 Dataset and Parameters

The image dataset used for calculating the effectiveness of algorithms belongs to the city of Bern, Switzerland captured by European Remote Sensing 2 satellite in the month of April and May 1999 as shown in Figure 2(a) and 2(b). Between the two dates, the Bern city and airport was flooded by Aare River. The ground truth has been shown in Figure 2(c).



(a) (b) (c)

Figure 2. Multi-temporal Images of Bern City (a) Image captured in April 1999 before Flooding (b) Image Captured in May 1999 after Flooding (c) Ground Truth[9].

The effectiveness of the proposed method is compared based upon percentage correct classification (PCC) and value of Kappa Coefficient (K_c)[19]. The value of Kappa coefficient lies between 0 and 1. Kappa coefficient is a measure of accuracy[20]. If Kappa value is 1 then it means that the change map is in 100% agreement with the reference map.

If Kappa value is 0 then it means that the change map and the reference map have no agreement.

$$PCC = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \quad (5)$$

$$A = \frac{((Tp + Fn) \, x \, (Tp + Fp) + (Fp + Tn) \, x \, (Tn + Fn))}{(Tp + Tn + Fp + Tn)^2} \quad (6)$$

$$Kc = \frac{PCC - A}{1 - A} \quad (7)$$

True positive (T_P) are the changed pixels which has been identified correctly as changed pixels. The value of (T_P) is 1 if the value of corresponding pixels in output of proposed algorithm and ground truth are both 1.Otherwise (T_P) will be zero. True negative (T_n) are the unchanged pixels which have been correctly identified as unchanged. The value of (T_n) is 1 if the corresponding pixels value in output of proposed algorithm and ground truth are both 0.Otherwise (T_n) will be zero. False positive (F_P) are those pixels which are actually changed but identified as unchanged pixels. The value of (F_P) is 1 if the pixels value in output of algorithm is 1 and the value of corresponding pixel in ground truth is 0.Otherwise (F_P) will be zero. False negative (F_n) are those unchanged pixels which have been identified wrongly as changed. The value of (F_n) is 1 if the pixels value in the output of algorithm is 0 and the value of corresponding pixel in ground truth is 1.Otherwise (F_n) will be zero.

3.2 Results and Discussion

The quantitative results of the change detection methods have been given in Table 1. It is clear that the proposed method has resulted in lowest overall error equal to 313, highest PCC equal to 99.65% and highest value of Kappa coefficient equal to 0.9954.

Table 1. Change Detection Results of Algorithms

Parameters	Method				
	Log Ratio	Mean Ratio	DWT-FCM	DWT-CIVB	Proposed
Fp	37	17115	507	131	145
Fn	293	6	61	218	168
OE	330	17121	568	349	313
PCC (%)	99.64	81.23	99.37	99.61	99.65
Kc	0.9952	0.7515	0.790	0.8524	0.9954

It means that the proposed method has been able to recover maximum changed and unchanged areas with highest accuracy. The maximum value of kappa coefficient indicates that the proposed method is in highest agreement with the ground truth image. The DWT-FCM is not able to recover the changed pixels accurately which resulted in lot of false positives. The PCC and Kappa Coefficient for DWT-FCM are 99.37% and 0.790 respectively. The PCC and Kappa value yielded by DWT-CIVB are 99.61% and 0.8524 respectively. This clearly shows that DWT-FCM and DWT-CIVB has generated lots of false alarms which lead to increase in overall errors. The performance of the proposed approach can also be analyzed by the change detection map obtained from different change detection methods as given in Figure 3(a)-3(f). As shown in Figure 3(a), the log ratio operator has resulted in lesser spot but lot of information has been lost because of the suppression of high frequency pixels. As can be seen from 3(b), change map generated by mean ratio operator has more spots. This is because of the presence of speckle noise. For the comparative analysis, the change map obtained from DWT-FCM and DWT-CIVB based methods has been shown in Figure 3(c) and 3(d) respectively. As shown in Figure 3(c), the change map generated contains many spots which mean which indicates the generation of false alarms. The change map obtained from DWT-CIVB has been shown in Figure 3(d) resulted in loss of information. However, the change map generated by proposed method has been shown in Figure 3(e). The proposed method has been able to recover the maximum changed and unchanged pixels with less speckle noise. Based upon the comparative visual analysis with the other methods, it is clear that the change map obtained from the proposed method has maximum resemblance with the ground truth shown in Figure 2(c).

The proposed method combines the spatial and grey information in the neighborhood which resulted in reduction of speckle noise in the fused image. The fused image contains maximum features of the source images. So, the It can be seen that the change detection map has recovered the maximum changed and unchanged pixels with less speckle noise. The proposed method offers least overall error and highest accuracy.

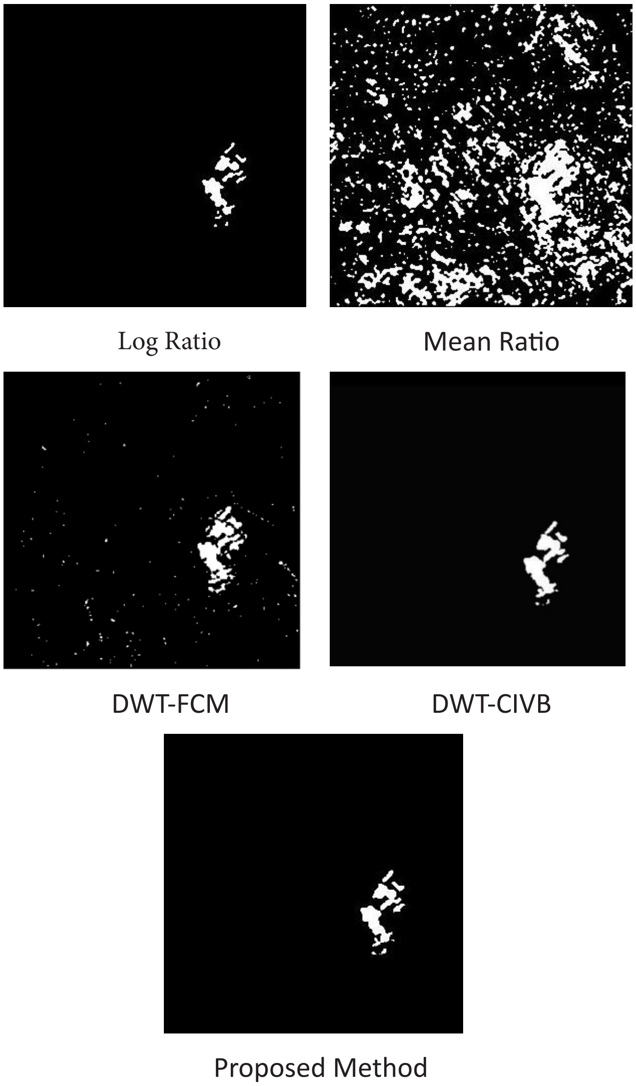


Figure 3. Change map of Ottawa data set generated by. (a) Log Ratio Operator (b) Mean Ratio Operator (c) DWT-FCM (d) DWT-CIVB (e) Proposed Method.

4. Conclusion

In this paper, new fusion rules for image fusion have been proposed. The source images obtained from mean ratio and log ratio have been fused using discrete wavelet transform. The low frequency sub-band has been fused using proposed average based fusion rule while high frequency sub-band has been fused using proposed neighborhood mean based fusion rule. The proposed rule utilizes the spatial and grey information in the neighborhood of the pixel to generate the fused image. The changed and unchanged areas are segmented using fuzzy c means clustering. The proposed method has been implemented on image dataset of the city of Bern. The performance of the algorithm has been compared with the state of the art algorithm like DWT-FCM and DWT-CIVB. The quantitative and qualitative results from the proposed algorithm find the reduction in overall error and speckle noise. The results also show that the PCC and Kappa value has been greatly improved. The experiment results prove that the performance of the proposed method is better than it preexistence.

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