International Journal of Electronics Engineering Research.
ISSN 0975-6450 Volume 9, Number 1 (2017) pp. 141-150

http://www.ripublication.com

Change Detection in Remotely Sensed Images Based on Image Fusion and Fuzzy Clustering

Er. Abhishek Sharma[1] and Dr. Tarun Gulati[2]

[1,2]Electronics and Communication Department, Maharishi Markandeshwar University, Mullana, Ambala, India.

Abstract

Change detection in remotely sensed images involves a multi-temporal dataset, an algorithm to detect the change and classification of the difference image into changed and unchanged regions. The quality of results mainly depends upon the algorithm used for change detection. In this paper, a Modified Discrete Wavelet Transform (DWT) based image fusion method for change detection has been proposed. The changed and unchanged areas are segmented by fuzzy c means clustering (FCM). The algorithm has been implemented in MATLAB R2013 on two datasets. The first dataset belongs to the Bi-temporal images of the area of Reno Lake. The first image was captured on August 5, 1986 and the second image was captured on August 5, 1992. The second dataset used is from the city of Ottawa. The results are compared based upon various parameters like Percentage correct classification or Accuracy (PCC) and Kappa coefficient (K_c). The qualitative and quantitative results show that the accuracy and Kappa value of proposed method is higher than the pixel averaging DWT based fusion method.

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

INTRODUCTION

Change detection in images involves comparing a set of images of a scene captured at different times to generate a difference image [1]. Such images are called as multi temporal images and the change occurred with time is known as temporal change. The change detection methods are mainly categorized as supervised and unsupervised change detection. Supervised change detection requires the ground level knowledge of the area undergone change like field survey reports and samples [2]. On the other hand, unsupervised change detection [3] is more popular as there is no such need of ground truth to detect the changes. The first step involved in image changed detection is the co-registration of images and preprocessing. Registration involves the alignment of corresponding pixels of both the images with one another. In the second step, the change detection method compares the co-registered images and generates a difference image. The last step is to apply segmentation algorithm on the difference image to generate a binary change map by classifying the changed and unchanged regions in different clusters. Many unsupervised change detection algorithms has been mentioned in the literature [3-6]. The most basic techniques used for change detection are differencing and ratioing. In image differencing, the corresponding pixel in one image is subtracted from the second. In image ratioing, the corresponding values of pixels in multi-temporal images are divided to get the output image. Out of these techniques, ratioing techniques are more popular because of their robustness to calibration errors[7]. However, this is also interesting to get enhanced images combining the features of different change detection methods by using a technique called image fusion. In the literature, much image fusion method has been presented in which the outputs of different techniques are fused to generate a difference image with high quality. Discrete level transform Stationary wavelet transform and Nonsubsampled contourlet transform based image fusion are the popular techniques for image fusion [8-10]. In image fusion, the source images are decomposed into four equal size images through discrete wavelet transforms. In the next step, the coefficients of low frequency sub-band and high frequency sub-band of the decomposed images are fused separately to obtain a fused coefficient map which has features of both the images. In the last step, inverse discrete wavelet transform is applied on the fused coefficient to get a fused image. Clustering technique is applied on the output of image fusion which classifies the changed and unchanged areas into different clusters. The changed areas belong to one cluster while the unchanged areas belong to the other. There are many clustering techniques in the literature like Fuzzy C means clustering [11-12], k means clustering [13] and Nonsubsampled contourlet transform (NSCT) based clustering [14].

This paper is organized into five sections. The next section introduces the methodology used for change detection. Third section introduces the datasets and parameters used for analysis. Fourth section presents the results and analysis. The fifth section presents the conclusion.

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 proposed approach 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 image fusion method based upon discrete wavelet transform. In the last step, the difference image is classified into changed and unchanged areas by fuzzy c means clustering algorithm. 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. The two images required for image fusion are obtained from means ratio and log ratio operators respectively.

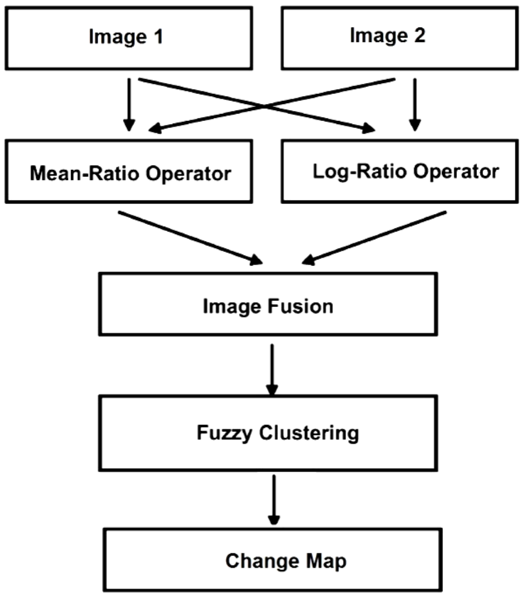


Figure 1: Methodology of proposed change detection approach

In Log Ratio operator, natural logarithms of the ratio of pixels in the images are calculated as given in equation no 1.Applying Log operator on an image enhances the low frequency components and suppressing the high frequency features in the output image.

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

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.

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

Where μ_1 *and* μ_2 in equation 2 represents the local mean value of the pixel in the neighborhood of first and second image respectively [7].

Image Fusion

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. Different fusion rules are applied on the low frequency and high frequency coefficients. In the next step, inverse discrete level transform (IDWT) is applied on the fused multiresolution representation to get the fused image. Finally, the output of Image fusion is segmented into two clusters by using fuzzy c means clustering.

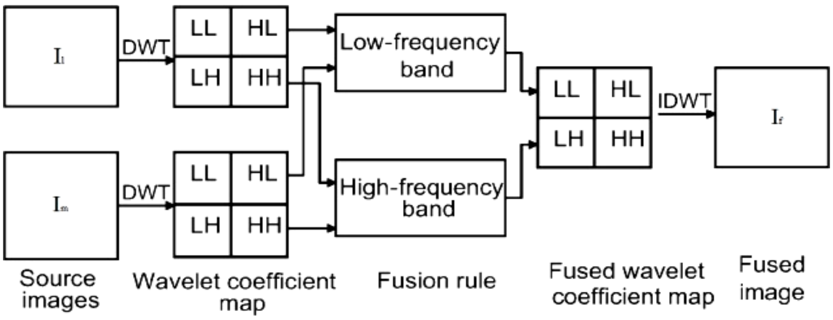


Figure 2: Flow chart of DWT based Image Fusion [8]

As shown in figure 2, the I_l and I_m denotes the output of log ratio and means ratio respectively. L stands for low pass filter while H stands for High pass filter. The approximate portion of the image is represented by LL while vertical, horizontal and diagonal portions of the image are denoted by HL, LH and HH respectively. I_f represents the fused image. The first step involved in the process is the decomposition of I_l and I_m into four images of the equal size. Image I^{LL} represents the approximate portion of the image while other images such as I^{HL}, I^{LH} and I^{HH} show the information about the lines and edges in the image. As the low frequency sub-band and high frequency sub-bands represents different features so it is necessary to fuse them through different fusion rules. There are many fusion rules which have been proposed in the literature. The main purpose of the fusion rules is to maximize the features in the fused image in correspondence with the source images. Here two fusion rules have been proposed:

Fusion Rule for Low frequency sub-band

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

Fusion Rule for high frequency sub-band

$$\mathrm{I}_{\epsilon}^{\mathrm{f}} = \min\left(\mathrm{I}_{\epsilon}^{\mathrm{l}}, \mathrm{I}_{\epsilon}^{\mathrm{m}}\right) \tag{4}$$

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 $I\varepsilon$(ε= HL, LH and HH) represents the coefficients of high frequency sub-band. 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, minimum of the coefficients in the source images is selected so as to suppress the background information . So based upon the proposed fusion rules, the change detection output results in maximum background suppression and enhanced features in the changed image.

Fuzzy Clustering

In fuzzy clustering the pixels under consideration are assigned to the desired number of clusters as per the degree of belongingness. Fuzzy C Means (FCM) is the basic among all the clustering algorithms [11]. The limitations in FCM lead to the development of other modified algorithms based upon FCM.

The basis of FCM is to minimize the objective function J_m as mentioned in Eq. 5.

$$J_m = \sum_{i=1}^{p}\sum_{k=1}^{q} u_{ik}^{n} \|y_i - r_k\|^2 \quad ,1 \leq \mathrm{n} \leq \infty \tag{5}$$

Where *n* is a positive real number. u_{ik} represents the value of membership of y_i which belongs to cluster k. y_j denotes the *i*th value of measured data. The centre of cluster is denoted by r_k and $\|y_i - r_k\|$ represents the similarity between the centre of cluster and measure data. The objective function is iteratively optimized to carry out the fuzzy partitioning based upon updation in r_k and u_{ik} given by

$$u_{ik} = \frac{1}{\sum_{k=1}^{q}\left(\frac{\|y_i - r_k\|}{\left\|y_i - r_j\right\|}\right)^{\frac{2}{\mathrm{n}-1}}} \tag{6}$$

$$r_k = \frac{\sum_1^p u_{ik}^n \cdot y_i}{\sum_1^q u_{ik}^n} \tag{7}$$

This iteration will continue till

$$\max_{ik} \left\{ \left| u_{ik}^{(j+1)} - u_{ik}^{(j)} \right| \right\} > \varepsilon \tag{8}$$

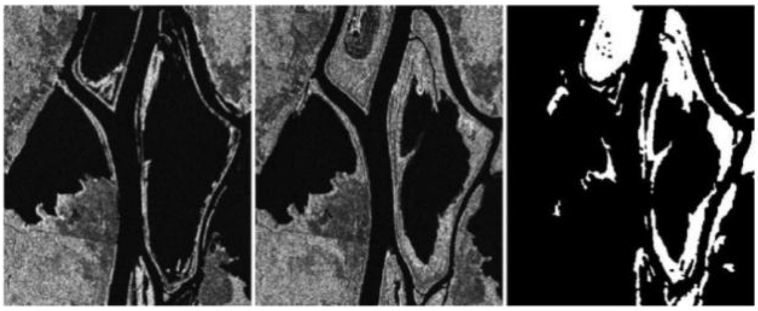
Where ε is any positive value less than 1 and j is the number of steps for which the iteration run.

DATASETS AND PARAMETERS

To compute the effectiveness of the proposed algorithms, multi-temporal image dataset has been used. One dataset belongs to the Reno Lake Tahoe areas with pixel size 200x200 captured on 5th August, 1986 and 5th August, 1992 as shown in figure 3(a) and 3(b) [15]. The images show the effect of draught on Reno Lake. The second dataset belong to Ottawa city captured in July 1997 and August 1997 as shown in figure 4(a) and 4(b) [8]. The ground truth has been generated by manual analysis.

(a) (b) (c)

Figure 3. Multi-temporal images of Reno Lake Tahoe area. (a) Image captured on 5th August, 1986 (b) Image captured on 5th August, 1992 (c) Ground truth



(a) (b) (c)

Figure 4. Multi-temporal images of Ottawa area (a) Image captured in July 1997 (b) Image captured in August 1997 (c) Ground truth

The effectiveness is compared based upon percentage correct classification (PCC) or accuracy to detect the changes and Kappa Coefficient (K_c) [16]. The value of Kappa coefficient lies between 0 and 1. Kappa coefficient is a measure of accuracy [17].

$$\mathrm{PCC} = \frac{(T_p+T_n)}{(T_p+T_n+F_p+F_n)} \tag{9}$$

$$\text{If} \quad A = \frac{\left((Tp+Fn) \times (Tp+Fp)+(Fp+Tn) \times (Tn+Fn)\right)}{(Tp+Tn+Fp+Tn)^2} \tag{10}$$

$$Kc = \frac{\mathrm{PCC} - A}{1 - A} \tag{11}$$

True positive(T_P) are the changed pixels which has been identified correctly as changed pixels by the change detection algorithm, True Negative) (T_n) are the unchanged pixels which have been correctly identified as unchanged, False Positive (F_P) are those pixels which are actually changed but identified as unchanged, False Negative (F_n) are those unchanged pixels which have been identified wrongly as changed.

RESULTS

In this section, the proposed technique is applied on the image datasets. The qualitative and quantitative results obtained from the proposed method and pixel averaging based image fusion method has been provided.

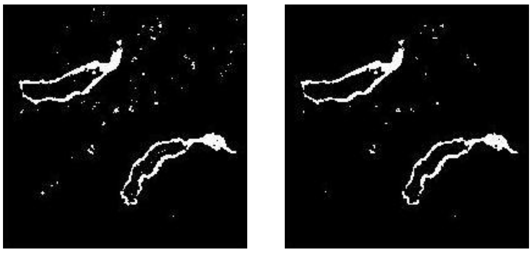
Results of Reno Lake Dataset

The quantitative and qualitative results obtained on applying the proposed technique on Reno Lake Dataset has been summarise in Table 1 and figure 5 respectively. The results of the proposed technique have been compared with the existing average based image fusion. For the sake of comparison in quantitative analysis, parameters like accuracy and kappa coefficient has been calculated. The results shows that the pixel averaging based image fusion method obtained 99.11% accuracy and value of kappa coefficient is 0.988. On the other hand, accuracy of proposed method is 99.44% and value of kappa coefficient is 0.992 which are higher than the pixel averaging based technique.

Table I. Comparison of fusion algorithm applied on Reno Lake data set.

S No	Fusion Method	PCC (%)	(K_c)
1	Pixel Averaging	99.11	0.98
2	Proposed Method	99.44	0.99

The change map obtained from pixel averaging and proposed method has been given in figure 5(a) and 5(b) respectively. As clearly seen that, the pixel averaging based method is not able to suppress the background information so resulting in more spots than the proposed method. If the change map obtained from both the techniques is compared with the ground truth then it is clear that the resemblance of change map from proposed method is higher than pixel averaging based method.



(a) **(b)**

Figure 5: Change maps on Reno Lake data generated by (a) Pixel Averaging (b) Proposed Method

The quantitative and qualitative analysis proves the effectiveness of proposed method higher than the existing pixel averaging based fusion method.

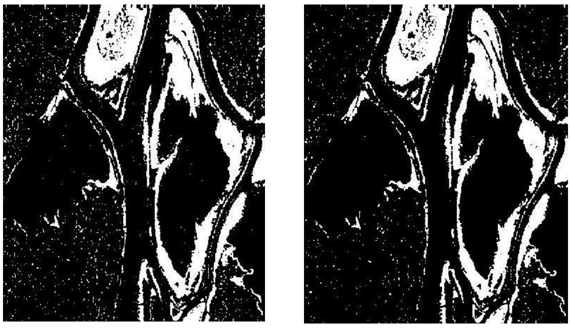
Results of Ottawa Dataset

The quantitative results of proposed algorithm and other existing algorithms for Ottawa dataset has been given in Tab 2. The accuracy and Kappa coefficient value of pixel averaging based image fusion method are 94.04% and 0.923 respectively while the accuracy of proposed method is 94.71% and kappa coefficient value is 0.934. So it is clear that the accuracy and Kappa coefficient value of the proposed method are better than the existing pixel averaging based method which proves the effectiveness of the proposed method for change detection.

Table II. Comparison of fusion algorithm applied on Ottawa dataset.

S No	Method	PCC (%)	(K_c)
1	Pixel Averaging	94.04	0.92
2	Proposed Method	94.71	0.93

The change map obtained from pixel averaging based image fusion method and proposed method has been shown in figure 6(a) and 6(b) respectively. The change map obtained from proposed method has higher resemblance with the ground truth.



(a) **(b)**

Figure 6: Change map of Ottawa data set generated by. (a) Pixel Averaging (b) Proposed Method

CONCLUSION

In this paper, image fusion method based on DWT has been proposed for change detection. Firstly, the source images have been generated by log ratio and mean ratio respectively. The source images are fused based upon the set of rules proposed in this paper. Fuzzy c means clustering has been applied to cluster the changed and unchanged areas. The methods have been implemented in MATLAB R2013. The qualitative and quantitative results obtained by the proposed algorithm have been compared with existing pixel averaging techniques. The results have been analyzed through datasets of Reno lake area and Ottawa area. The quantitative and qualitative analysis proves that the accuracy and kappa value of the proposed algorithm is better than the other methods. As far as qualitative comparison is concerned, the proposed methods offer the least spots. So, based upon the analysis of results it is concluded that the proposed algorithm produce the best results for change detection.

REFERENCES

[1] R. J. Radke et al. “Image change detection algorithms: A systematic survey,” IEEE Trans. Image Process., vol. 14, no. 3, pp. 294–307, Mar. 2005.

[2] Michele Volpi et al. “Supervised change detection in VHR images using contextual information and support vector machines”, International journal of applied earth observation and geoinformation, vol. 20, pp. 77-85, Feb 2013.

[3] Turgay Celik. “Unsupervised multiscale change detection in multitemporal synthetic aperture radar images”, Signal processing conference, 17th European, pp. 1547-1551, 2009.

[4] Rouhollah Dianat. "Change Detection in Optical Remote Sensing Images Using Difference-Based Methods and Spatial Information", IEEE Geoscience and Remote Sensing Letters, vol. 7, Issue- 1, pp. 215 - 219, 2010.
[5] Johnson, R. D., et. al. "Change vector analysis: a technique for the multispectral monitoring of land cover and condition", International Journal of Remote Sensing, pp. 411–426, 1998.
[6] Francesca Bovolo, et. al. "A Framework for Automatic and Unsupervised Detection of Multiple Changes in Multitemporal Images", IEEE Transactions on Geoscience and Remote Sensing, vol. 50, Issue-6, pp. 2196 – 2212, 2012.
[7] Abhishek Sharma et. al. "Review of change detection techniques for remotely sensed images", International Journal of computer science and engineering, vol.-5, Issue-1, pp. 22-25, Jan 2017.
[8] Maoguo Gong et al. "Change detection in synthetic aperture radar images based on Image fusion and fuzzy clustering", IEEE transaction on image processing, vol.-21, Issue-4, pp. 2141-2151, April 2012.
[9] P. Borwonwatanadelok et. al. "Multi Focus image fusion based on stationary wavelet transform and extended spatial frequency measurement", IEEE transaction on electronic computer technology. pp. 77-81, 2009.
[10] Shutao Li et. al. "Multitemporal image change detection using a detail enhancing approach with nonsubsampled cntourlet transform", Geoscience and remote sensing letters, vol.-9, Issue-5, pp. 836-840, Sept 2012.
[11] J. C. Bezdek. "Pattern Recognition with Fuzzy Objective Function". New York: Plenum, 1981.
[12] J. C. Dunn. "A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters", Journal of Cybernetics, vol.- 3, pp. 32-57, 1973.
[13] Turgay Celik. "Unsupervised change detection in satellite images using principal component analysis and k means clustering", IEEE Geoscience and remote sensing letters, Vol.-6, Issue-4, pp. 772-776, 2009.
[14] A. L. da Cunha et al.. "The nonsubsampled contourlet transform: Theory, design, and application," IEEE Tranactions on Image Processing.,vol.- 15, Issue- 10, pp. 3089–3101, Oct. 2006.
[15] http://geochange.er.usgs.gov/sw/changes/natural/reno-tahoe/index.html
[16] Rosin P.L., Ioannidis E. "Evaluation of global image thresholding for change detection", Pattern Recognition Letters, 24(14), pp. 2345–2356, 2003.
[17] G. H. Rosenfield and A. Fitzpatrick-Lins. "A coefficient of agreement as a measure of thematic classification accuracy", Photogramm. Eng. Remote sensing, vol. 52, Issue-2, pp. 223-227, 1986.