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

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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 (Κc). 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 Nonsampled 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 Nonsampled 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 $R \times C$, 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.

\[ I_l(x, y) = \log \frac{I_1(x, y)}{I_2(x, y)} \]  

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.

\[ I_m(x, y) = 1 - \min \left( \frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1} \right) \]  

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.
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 [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.

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 \( I_{HL}, I_{LH}, I_{HH} \) 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**

\[
I_{LL}^f = \alpha \cdot \max(I_{LL}^l, I_{LL}^m) + (1 + \alpha) \cdot \frac{(I_{LL}^l + I_{LL}^m)}{2}
\]  

(3)

**Figure 2:** Flow chart of DWT based Image Fusion [8]
Fusion Rule for high frequency sub-band

\[ I^f_{\epsilon} = \min(I^l_{\epsilon}, I^m) \]  

(4)

Here \( \alpha \) 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 \( I_\epsilon(\epsilon=\text{HL}, \text{LH} \text{ and } \text{HH}) \) 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.

\[ J_m = \sum_{i=1}^{p} \sum_{k=1}^{q} u_{ik}^n \|y_i - r_k\|^2, 1 \leq n \leq \infty \]  

(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

\[ u_{ik} = \frac{1}{\sum_{k=1}^{q} \left( \frac{\|y_i - r_k\|^2}{n-1} \right)^{\frac{n-1}{2}}} \]  

(6)

\[ r_k = \frac{\sum_{i=1}^{p} u_{ik}^n y_i}{\sum_{i=1}^{p} u_{ik}^n} \]  

(7)
This iteration will continue till

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

(8)

Where $\varepsilon$ 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.

![Figure 3](image1.png)

(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

![Figure 4](image2.png)

(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
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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].

\[
PCC = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)}
\]

\[
A = \frac{((T_p + F_n) \times (T_p + F_p) + (F_p + T_n) \times (T_n + F_n))}{(T_p + T_n + F_p + T_n)^2}
\]

\[
K_c = \frac{PCC - A}{1 - A}
\]

True positive ($T_p$) are the changed pixels which have 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 have been summarised 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 show 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>
<thead>
<tr>
<th>S No</th>
<th>Fusion Method</th>
<th>PCC (%)</th>
<th>($K_c$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pixel Averaging</td>
<td>99.11</td>
<td>0.98</td>
</tr>
<tr>
<td>2</td>
<td>Proposed Method</td>
<td>99.44</td>
<td>0.99</td>
</tr>
</tbody>
</table>
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.

![Change maps on Reno Lake data generated by (a) Pixel Averaging (b) Proposed Method](image)

**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>
<thead>
<tr>
<th>S No</th>
<th>Method</th>
<th>PCC (%)</th>
<th>(Kc)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pixel Averaging</td>
<td>94.04</td>
<td>0.92</td>
</tr>
<tr>
<td>2</td>
<td>Proposed Method</td>
<td>94.71</td>
<td>0.93</td>
</tr>
</tbody>
</table>

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

![Change map of Ottawa data set generated by. (a) Pixel Averaging (b) Proposed Method](image)

**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**


