

Research Article

A Decision Making Framework using Advanced Change Detection in Satellite Images

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Abstract

The detection of changes occurring on the earth surface through the use of multitemporal remote sensing images is one of the most important applications of remote sensing technology. In several applications (e.g. disaster management, deforestation, crop development, urban growth), the remote sensing-based change detection using multitemporal satellite images is crucial. Particularly, in disaster management cases, the fast and accurate detection of affected regions in multitemporal images acquired at two different time instances, i.e., before and after the disaster, plays a very essential role in taking timely and appropriate decisions. In such cases the change detection method to produce the change results with almost no manual interventions in a reasonable time interval is very important. In this paper, a robust unsupervised change-detection method is proposed. Here, two multitemporal images are taken as input images, geometric and radiometric corrections are performed on one image relative to the other image. Discrete Wavelet Transform (DWT) is applied on both images and then image difference is taken by subtraction. Then features are extracted from difference image using Principal Component Analysis (PCA). Changed and unchanged pixels are separated then by using k-means clustering algorithm with $k=2$.

Keywords: Remote Sensing, Satellite Images, Change detection, Image differencing, Unsupervised Approach, DWT, PCA, k-means clustering.

1. Introduction

During past decade, the ever increasing availability of multitemporal satellite images resulted in the applications related to environmental monitoring as well as land cover control and management. Most of these applications are associated with the analysis of dynamic phenomena that occur at different scales and result in changes on the Earth surface.

Change detection methods are classified as either supervised or unsupervised according to the nature of data processing. Supervised method is based on a supervised classification, which requires the availability of a ground truth data in order to derive a suitable training set for the learning process of classifiers. The latter approach, which is adopted in this paper, performs change detection by making a direct comparison of two multitemporal images considered without incorporating any additional information.

Unsupervised change detection techniques mainly use the automatic analysis of change data which are constructed using multitemporal images. The change data are generally created using one of the following methods image differencing, Wavelet Transform (Turgay Celik and Kai-Kuang Ma *et al*, 2010), change vector analysis (F. Bovolo and L. Bruzzone *et al*, 2007), principal component

analysis (PCA) (T. Celik *et al*, 2009), image rationing. Several unsupervised change detection techniques have been proposed in the literature falling in these categories which use complicated data modeling and parameter estimation.

Preprocessing of satellite images prior to image change detection is essential. Preprocessing commonly comprises a series of sequential operations, including atmospheric correction or normalization, image registration, geometric correction, and masking (e.g., for clouds, water, irrelevant features) (Lt.Dr.S.Santhosh Baboo, M.Renuka Devi *et al*, 2011). Preprocessing of image data often will include radiometric correction (Xuexia Chen, Lee Vierling, Don Deering *et al*, 2005) and geometric correction.

Radiometric corrections are made to the raw digital image data to correct for brightness values, of the object on the ground, that have been distorted because of sensor calibration or sensor malfunction problems. The distortion of images is caused by the scattering of reflected electromagnetic light energy due to a constantly changing atmosphere. This is one source of sensor calibration error.

Geometric corrections are made to correct the inaccuracy between the location coordinates of the picture elements in the image data, and the actual location coordinates on the ground. Several types of geometric corrections include system, precision, and terrain corrections (Lt.Dr.S.Santhosh Baboo, M.Renuka Devi *et al*, 2011).

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Most of the unsupervised methods are developed based on the image differencing. Image differencing-based algorithms accomplish the change detection by subtracting the pixel from, the images acquired at two time instances to produce new image called *difference image*. The computed difference image is such that the values of the pixels associated with land cover or land use changes present values significantly different from those of the pixels associated with unchanged areas (T. Celik *et al* , 2009).

In this paper, a computationally simple yet effective automatic change detection method is proposed by analyzing the difference image of two satellite images acquired from the same area coverage but at two different time instances. The nonoverlapping blocks of the difference image are used to extract eigenvectors by applying PCA (R. C. Gonzalez and R. E. Woods *et al*, 2006). Then, a feature vector for each pixel of the difference image is extracted by projecting its $h \times h$ neighborhood data onto eigenvector space. The feature vector space is clustered into two clusters using k-means algorithm (R. C. Gonzalez and R. E. Woods *et al*, 2006). Each cluster is represented with a mean feature vector. Finally, change detection is achieved by assigning each pixel of the difference image to the one of the clusters according to the minimum Euclidean distance between its feature vector and mean feature vector of the clusters (T. Celik *et al* , 2009).

2. Proposed Methodology

The process of unsupervised change detection is summarized in the flowchart below:

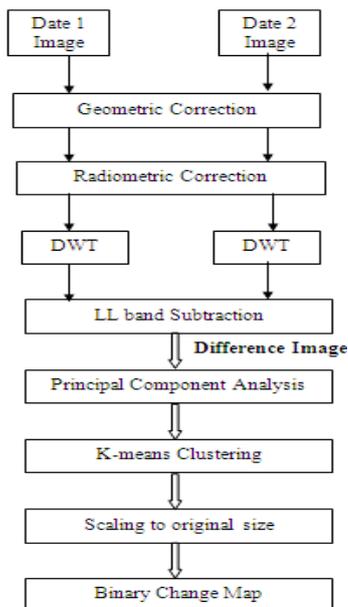


Figure 1 Proposed System

Before any change detection algorithm can be applied to satellite images, they need to be corrected for geometric and atmospheric differences. This is called geometric and radiometric correction. Steps shown in fig 1 are explained in brief as:

Geometric Correction: The purpose of geometric correction or co-registration is to remove the influence of different geometries in the images. In order to accomplish this, a number of ground control points (GCPs) must be collected. A GCP is an element in one image that is in the same location in another image.

- This location can never be measured exactly, so the RMS (root mean square) error of the GCP collection must be under, usually 0.5 pixels. RMS error is calculated according to the following equation: $RMS_{error} = \sqrt{(x' - x_{orig})^2 + (y' - y_{orig})^2}$

Where x' , y' represent the estimated coordinates in the geometrically corrected image and x_{orig} , y_{orig} represent the coordinates of the GCPs.

- **Radiometric Correction:** There are two kinds of radiometric correction, absolute and relative. For absolute radiometric correction, data concerning the atmosphere at the time of image acquisition is needed. As this data is very difficult to obtain, relative radiometric correction is often used instead, where the digital values (DN) of images are transformed to a common scale. There are different methods of relative radiometric correction statistical adjustments, histogram matching and linear regression normalization. In histogram matching one image's histogram is matched to that of another image and in linear regression normalization technique a base image is the reference image that the target image (the other image) needs to be related to. The linear function can be expressed as $y = ax + b$

Where a and b are constants and x is the image band being normalized.

- **Discrete Wavelet Transform (DWT):** The next stage of the algorithm is decomposing both the images separately using S level UDWT (Undecimated Discrete wavelet Transform). The UDWT is the decomposition of image D which creates four subbands which can be labeled as D_s, ll , D_s, lh , D_s, hl , and D_s, hh at each level s of the decomposition.

The two-level UDWT decomposition (hence $s = \{1, 2\}$) of the image is shown in Fig. 4.6, where l and h are 1-D low-pass and high-pass filters, respectively. The D_s, ll subband comes from the low-pass filtering along rows and columns of the image and is approximation of the D . The remaining pieces D_s, lh , D_s, hl , and D_s, hh are called as detailed components and are produced using low-pass and high-pass filtering alternatively. To obtain the next level of decomposition (i.e., $s + 1$ from s), subband D_s, ll alone is further decomposed to produce D_{s+1}, ll , D_{s+1}, lh , D_{s+1}, hl , and D_{s+1}, hh . This process continues until some final scale (S) is reached (Lt.Dr.S.Santhosh Baboo, M.Renuka Devi *et al*, 2011). The sub band images are shown in fig. 2.

- **Image Differencing:** After performing geometric and radiometric corrections and DWT, we have to calculate the difference image from two multitemporal input images. It is performed by subtracting, on a pixel basis, the images acquired at two time instances to produce new image called difference image. The computed difference image is

such that the values of the pixels associated with land cover or land use changes present values significantly different from those of the pixels associated with unchanged areas. Changes are then identified by analyzing the difference image.

- **Principal Component Analysis (PCA):** Difference image is divided into 5 x 5 non overlapping blocks and feature vector space is created using PCA. PCA (Principle Component Analysis) is defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance comes to lie on the first coordinate, the second greatest variance on the second coordinate and so on. Each Coordinate in Principle Component Analysis is called Principle Component. $C_i = b_{i1}(x_1) + b_{i2}(x_2) + \dots + b_{in}(x_n)$ Where, C_i is the i^{th} principle component, b_{ij} is the regression coefficient for observed variable j for the principle component i and x_i are the variables/dimensions.

Steps to find Principle Components:

1. Adjust the dataset to zero mean dataset.
 2. Find the Covariance Matrix.
 3. Calculate the normalized Eigenvectors and Eigenvalues of covariance matrix.
 4. Sort the Eigenvectors according to Eigenvalues from highest to lowest.
 5. Form the Feature vector F using the transpose of Eigenvectors.
 6. Multiply the transposed dataset with F.
- **Change detection / Analysis:** All the unsupervised techniques produce a difference image. This image must be analyzed to find the changes as well as to control variances caused by differences in variables that are not of interest. It also measure changes caused by variances in the variables of interest. Feature vectors are to be created by using PCA (Principal component analysis). Then analysis of the difference image can be performed using:
 - Manual trial-and error.
 - Empirical thresholding techniques.
 - Bayesian decision theory.
 - K-means Clustering

Algorithm for k-means clustering

- 1) Randomly select 'c' as a cluster centers.
- 2) Calculate the distance between each data point and cluster centers 'c'.
- 3) Assign the data point to the cluster center whose distance from the cluster center 'c' is minimum of all the cluster centers..
- 4) Recalculate the new cluster center using:

$$v_i = (1/c_i) \sum_{j=1}^{c_i} x_j$$

where, 'c_i' represents the number of data points in i^{th} cluster.

- 5) Recalculate the distance between each data point and new obtained cluster centers.
- 6) If no data point was reassigned then stop, otherwise repeat from step 3.

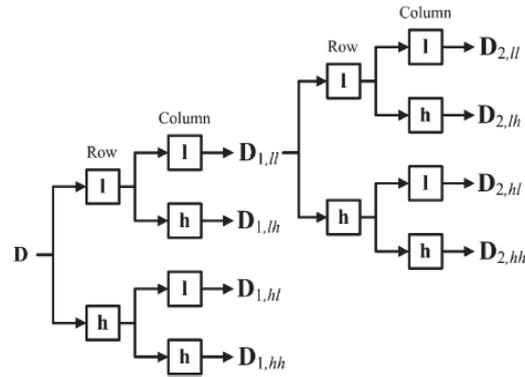


Figure 2 Two-levels UDWT decomposition filter bank structure

3. Experiments and Results

Two images of uttarakhand disaster 2013 are taken for experimentation.. Pre-disaster image of size 429 x 657 and post-disaster image is of size 436 x 657.

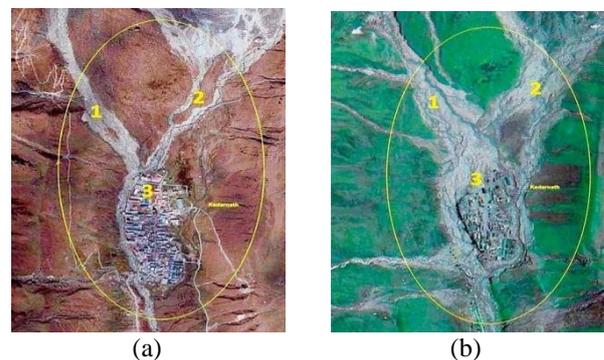
Step 1: Geometric Correction: Control points are selected from both the images. For each control point pair (x1, y1), (x2,y2) , angle and scale is calculated as,
 $angle = (180/\pi) * atan2(dy, dx)$
 $scale = 1 / \sqrt{dx^2 + dy^2}$

Step 2: Radiometric Correction: DN values of both images are transformed to same scale.

Step 3: DWT: Two –level DWT is applied on both the images.

Step 4: Image differencing: one image is subtracted from second image.

Step 5: PCA and K-means Clustering: The difference image is partitioned into $h \times h$ nonoverlapping blocks. $S, S \leq h^2$, orthonormal eigenvectors are extracted through PCA of $h \times h$ nonoverlapping block set to create an eigenvector space. Each pixel in the difference image is represented with an S-dimensional feature vector which is the projection of $h \times h$ difference image data onto the generated eigenvector space. The change detection is achieved by partitioning the feature vector space into two clusters using k-means clustering with $k = 2$ and then assigning each pixel to the one of the two clusters by using the minimum Euclidean distance between the pixel's feature vector and mean feature vector of clusters (T. Celik *et al* , 2009). In this paper, results are shown by carrying out experiment by using $h=5$ and $S=3$ which give better results as compared to other values of h and S .



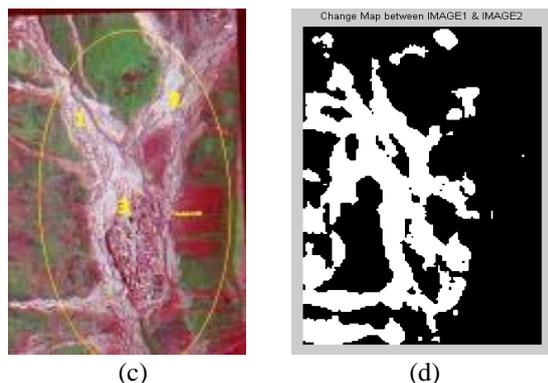


Figure 3 Change detection of images (a)Pre disaster image (b)Post disaster image (c) Geometrically and radiometrically corrected Post disaster image (d) Difference image after applying Proposed Method

4. Performance Evaluation

To conduct quantitative (or objective) performance evaluation, the ground truth needs to be established as follows: First, we choose the first image shown in the Fig. 7.1(a) as X1, and the pixel intensity values of X1 in an arbitrarily chosen region of interest (ROI) are modified to create the second test image X2. It guarantees that the absolute-valued difference between X1 and X2 is the selected ROI area. The test image X1 manually created test image X2 by modifying an ROI on X1, and the resulted ground truth of the binary change-detection mask is shown in Fig. 4 (a)–(c), respectively (Turgay Celik and Kai-Kuang Ma *et al*, 2010).

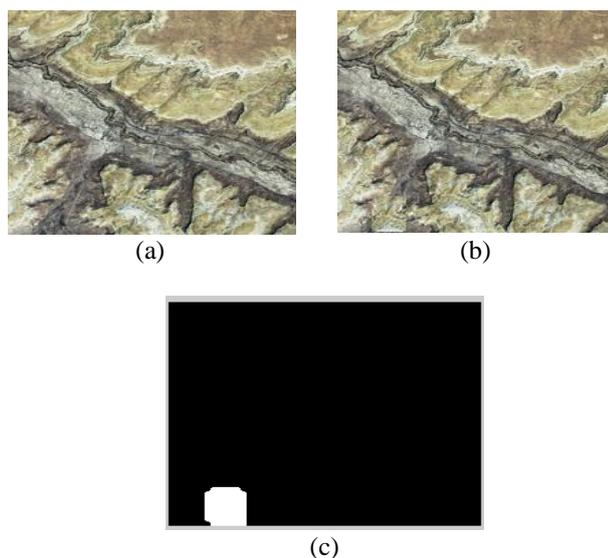


Figure 4 Change-detection performance evaluation with a manually created ground truth: (a) Test image X1, (b) created test image X2 by modifying an ROI on X1 (c) the binary change detection mask.

Once the binary change-detection mask has been obtained, the following defined quantities are computed for comparing the computed change-detection mask against the ground truth change-detection mask (Turgay Celik and Kai-Kuang Ma *et al*, 2010).

Let N be the total number of pixels

1) *True positives (TP)*: The number of “changed” pixels that were correctly detected. Probability of TP, PTP is given as,

$$PTP = TP/N$$

2) *False positives (FP)*: The number of “unchanged” pixels that were incorrectly detected as “changed” (also known as *false alarms*). Probability of FP, PFP is given as,

$$PFP = FP/N$$

3) *True negatives (TN)*: The number of “unchanged” pixels that were correctly detected. Probability of TN, PTN is given as,

$$PTN = TN/N$$

4) *False negatives (FN)*: The number of “changed” pixels that were incorrectly detected as “unchanged” (also known as *miss detections*). Probability of FN, PFN is given as,

$$PFN = FN/N$$

Therefore, the performance of the proposed algorithm can be measured in terms of the *correct classification (PCC)* and the *false classification (PFC)* which are, respectively, defined as ,

$$PCC = PTP + PTN$$

$$PFC = PFP + PFN$$

Performance evaluation of this method is summarized in Table I.

Table 1 Performance Evaluation of Proposed Method

Actual no. of change Pixels	Calculated no. of change Pixels	TP	FP	TN	FN	PCC (Accuracy) (%)
30923	30213	30213	0	426293	710	99.84
483	1132	483	649	42132	0	98.5
3337	898	898	0	435959	2439	99.44
800	1061	800	261	42203	0	99.4
3337	1511	1511	0	435959	1826	99.58
728	1154	728	426	42110	0	99.01

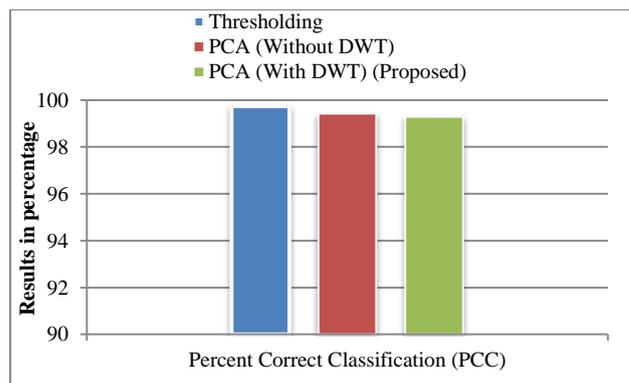


Figure 5 Graph showing comparison of PCC for all three methods

Performance evaluation for noisy input image

Many times satellite images are noisy. To check performance of proposed method against noise, salt and pepper noise is added in one of the input images and from the results shown in figure 6, visually it is clear that the proposed method is robust to noise.

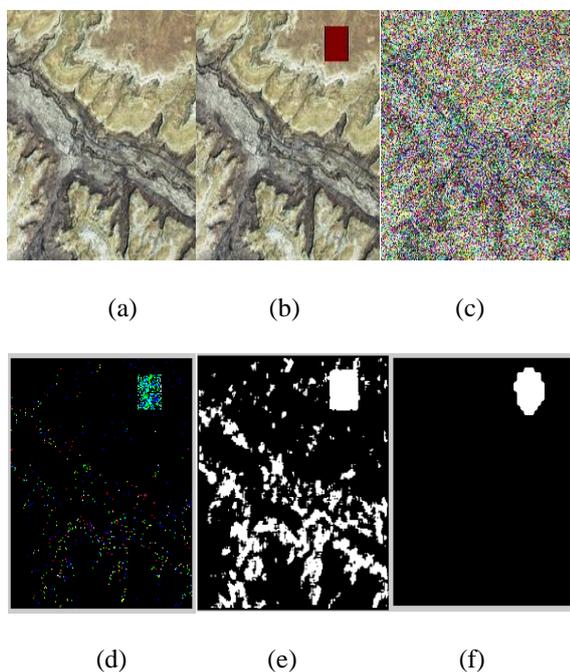


Figure 6 (a) Image 1 (b) Image 2 (c) Noise added to image 1 (d) Thresholding Result (e) PCA with k-means results (f) Proposed Method Results

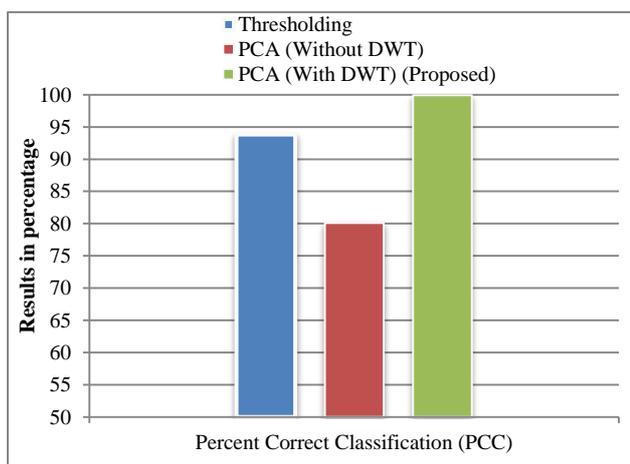


Figure 7 Graph showing comparison of PCC for all three methods

Conclusions

In proposed method, two level discrete wavelet transform (DWT) is applied on the input images and LL sub band of both images is used for further processing. Then difference image is obtained by subtracting LL sub bands of the input images. On this difference image, PCA and k-means clustering is applied as explained above and binary change map is generated.

As two level DWT is applied on input images in this method and only LL sub band is used for further computations, number of pixels in the difference image are reduced to approximately 1/16th of the difference image calculated without applying DWT. Results and graphs show that even though the accuracy of the proposed method is slightly less than that of directly using PCA and k-means clustering without applying DWT, the number of computations are drastically reduced. Also results of proposed method for noisy input images are better than that of PCA and k-means clustering without DWT because noise is high frequency component and we are removing high frequency components from input images and only taking low-low sub band from both input images, so noise is filtered after applying DWT.

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