Unsupervised Change Detection of Multispectral Images using Wavelet Fusion and Kohonen Clustering Network

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Abstract— **In this paper, an unsupervised change detection technique of multispectral images based on wavelet fusion and Kohonen Clustering Network is presented. The proposed method fuses absolute difference and change vector analysis image using wavelet fusion rules. The fused image highlights the changed areas while suppress unchanged areas. The Kohonen clustering network is used to create the final change map with changed areas highlighted. The performance of the proposed method was tested on two Landsat 5 TM images of Alaska region. The results obtained were compared with some other existing state of the art methods and it is observed that the proposed method outperforms the other methods.**

Keyword- CVA, Wavelet Fusion, Absolute Difference , Kohonen Clustering Network

I. Introduction

In remote sensing, change detection aims at identifying the changes that have occurred in an area by observing it at two different times. An important problem of image processing is to effectively remove noise from an image while keeping its features[1,2]. Change detection has been widely used to assess shifting cultivation, deforestation, urban growth, impact of natural disasters like Tsunamis, earthquakes and use/land cover changes etc. Change detection methods are based on supervised and unsupervised classification. Supervised classification based methods require training set for the learning of classifiers for identification of changes. Supervised methods have a serious limitation that the accuracy of these methods is highly dependent on the choice of training patterns, also these methods are time consuming. Thus, it is a good idea to move towards unsupervised change detection which does not require any training data rather it uses the spectral properties of the image to classify the image into different classes.

Change detection methods based on unsupervised methods include image differencing, change vector analysis (CVA) , principal component analysis (PCA), image rationing, normalized difference vegetation index etc[3]. A context specific and distribution free unsupervised technique was proposed which was based on modified Hopfield network to model spatial correlation between neighbouring pixels of the difference image [4]. An unsupervised method, split based approach (SBA) used large size multitemporal images to recognize different levels of damages resulting from tsunami along coastal areas of Indonesia. Initially large size image was split into sub images, then these sub images were analyzed and finally a split based threshold selection procedure was applied to identify changes [5].Unsupervised change detection based on semisupervised SVM and a similarity measure was proposed where spectral channels of multitemporal images were jointly analyzed in the original feature space without any training data. A selective Bayesian thresholding was used to develop pseudo training set for initializing binary semisupervised SVM [6]. A change detection method based on principal component analysis (PCA) and k-means clustering is presented in [7]. Change detection has also been done using genetic algorithm by minimizing a cost function, where cost value was taken as weighted sum of MSE of changed and unchanged pixels [8]. A neighbourhood based ratio approach was proposed in which neighbourhood ratio (NR) operator was used to produce difference image by combination of gray level information and spatial information of neighbouring pixels. This method proved superior to traditional ratio operator and log ratio operator [9]. Transform domain techniques have also been applied in change detection methods to analyze the difference image. Transforms like Undecimated Discrete Wavelet Transform (UDWT), Non subsampled Contourlet Transform have been applied. An unsupervised detail enhancing approach with non-subsampled contourlet transform (NSCT) is recently proposed. Difference image created using multitemporal images is decomposed into low pass approximation and high pass directional sub bands using non subsampled contourlet transform. Meaningful details of difference image are extracted by the fusion of directional sub bands. Extracted details are added to the base image selected from directional sub bands. Thus resulting in a detail enhanced difference image. PCA and k-means clustering are then applied [10]. Another change detection technique using Local Gradual Descent (LGDM) was proposed in which the difference image is partitioned into non overlapping blocks. Gaussian mixture model (GMM) with two components (changed and unchanged) was used for modeling the data distribution of difference image. LGDM modifies the pixel values of the sample to move it towards correct Gaussian component. Finally categorization of pixel is done by k-means clustering [11].

Many techniques have been proposed which provide spectral change information of the image. Every method has its own applicability for different areas and data sources. A single method does not provide satisfactory result. Thus in this paper, a novel technique based on wavelet fusion of absolute differencing and change vector analysis (CVA) images is proposed. The proposed method performs fusion of two difference images obtained by absolute differencing and CVA technique using wavelet fusion rules. The fused images are used to obtain the change map highlighting changed areas using Kohonen Clustering network(KCN).

II. PROPOSED WORK

Consider two bi temporal images, I_{T_1} and I_{T_2} of size p × q of the same geographical area taken at different times T_1 and T_2 .The proposed method contains the following steps: 1) creation of spectral change difference (SCD) image. 2) Wavelet fusion. 3) Clustering using KCN. 4) Formation of change map. The flow chart of the algorithm is shown in Fig.1

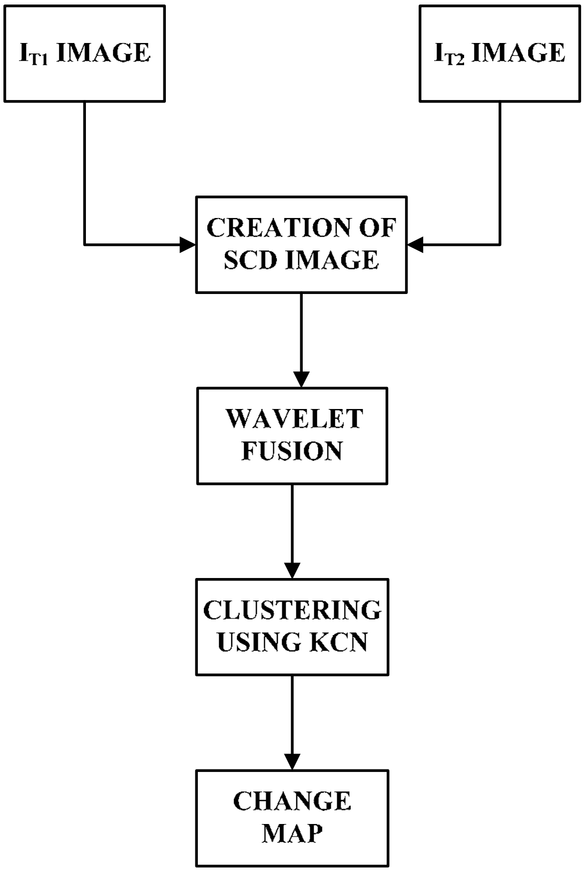


Fig.1 Flow chart of the proposed method

A. *Creation of SCD images*

Two algorithms are used to extract the changes in the two input images, namely absolute differencing[3] and change vector analysis[12] to create two difference images I_{AD} and I_{CVA} .

1) Absolute Differencing**:** Difference image created using Absolute Differencing is as follows:

$$I_{AD} = \sum_{k=1}^{M} I_{T_1}^k - I_{T_2}^k \quad , \text{for} \quad k = 1,2, \dots \dots M \qquad (1)$$

where $I_{T_1}^k$ and $I_{T_2}^k$ are the pixel reflectance spectra of k_{th} band at time T_1 and T_2 and M is the number of bands. In the difference image created by absolute differencing, higher grey values are assigned to changed areas while grey level values for unchanged areas are near zero.

2) Change Vector Analysis (CVA): CVA is the modulus of the difference between spectral feature vectors associated with each pair of corresponding pixels in the two images (of same geographical area and taken over different time instants). Each pixel in resulting difference image is represented by spectral change vector that allows creating difference image by using several bands. The advantage of CVA is that the reflectance properties of various bands of image can be combined. CVA of input images is calculated as:

$$I_{CVA}(x,y) = \sqrt{\sum_{k=1}^{M} (I_{T_1}^{k}\ (x,y) - I_{T_2}^{k}\ (x,y))^2} \qquad \text{for} \qquad k = 1,2 \ldots . M \qquad (2)$$

where $I_{CVA}(x,y)$ denotes the gray value of $(x,y)th$ pixel in the difference image that has been generated from corresponding pixels of images I_{T_1} and I_{T_2} having M bands.

B. Wavelet Fusion

Image fusion is a technique which combines information from several images to obtain an image with higher amount of information. Fusion techniques have been mainly applied at pixel level of image. A multiscale transform known as discrete wavelet transform (DWT) is widely used for image fusion. In this paper, DWT has been chosen for fusion as it preserves image details in both spatial and temporal domain [13, 14]. In wavelet fusion, DWT of Absolute Differencing I_{AD} and change vector analysis I_{CVA} images are taken. Wavelet Coefficients of low frequency subband of absolute differencing and change vector analysis (CVA) images are fused together according to the given fusion rule. To enhance the information of changed region and suppress the background information, the fusion rule given in eq.(3) is used.

$$I_{fu} \;=\; \eta\, I_{AD}^{LL} + \;+ \nu\, I_{CVA}^{LL} \qquad (3)$$

$$\eta \;=\; min\,(|I_{AD}^{LL}|\,, |I_{AVG}|\,)/max\,(\,|I_{AD}^{LL}|, |I_{AVG}|) \qquad (4)$$

$$\nu \;= (1 - min(\,|I_{AD}^{LL}|\,, |I_{AVG}|\,))/max\,(|I_{AD}^{LL}|\,, |I_{AVG}|\,) \qquad (5)$$

where I_{AD} and I_{CVA} indicate absolute difference and change vector analysis images, I_{fu} denotes fused image, η and ν are the weights for absolute and CVA difference images. I_{AD}^{LL} represents the low frequency coefficients of absolute differencing image, I_{CVA}^{LL} represents the low frequency coefficients of change vector analysis image and I_{AVG} is the mean value of low frequency coefficients of absolute difference and change vector analysis images. Finally, inverse DWT is taken to get the required fused image. One step decomposition of absolute distance and change vector difference images has been done as shown in Fig.2.

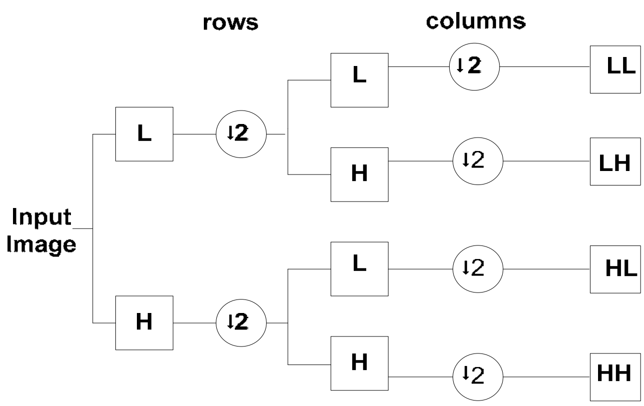


Fig.2 One Step Decomposition using DWT

C. Kohonen Clustering Network

The KCN is simplest neural network, without any activation function and hidden layer. The network has only two layers, i.e., input layer and output layer. The neuron closest to the input vector in terms of Euclidean distance is the winner neuron. The weight of the winner and its predefined neighbors are updated using a learning rule. The final change map is formed by clustering of fused difference image into two clusters of changed and unchanged using Kohonen Clustering Network (KCN) [15]. The network used for change detection in this paper is shown in Fig.3.

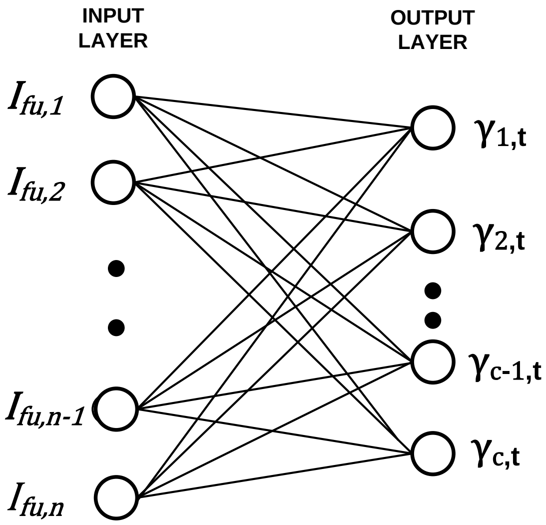


Fig.3 Architecture of KCN

Let the pixels of I_{fu} be represented by $I_{fu,j} \in (I_{fu,1}, I_{fu,2}, \dots\dots, I_{fu,n})$, where $n = pq$ is the total number of pixels in the image. These pixels are given as input to the KCN network. Centers of the clusters formed are denoted by $\gamma_{i,t}$.

Step1.**Initialization**: Initialize the cluster center $\gamma_{i,0}$ $(1 \le i \le c)$, learning rate $\beta_{ij,t}$ $(0 < \beta_{ij,t} < 1)$, threshold ε $(\varepsilon > 0)$ and topological neighborhood parameters. Set t = 1 and maximum iteration limit t_{max}.

Step2.**Selection of winner**: Calculate the squared Euclidean distance :

$$d_{ij,t}^2 = \left\| I_{fu,j} - \gamma_{i,t} \right\|^2 \ for\ j = 1, 2, \dots n \ \ and\ \ i = 1, 2, \dots c \qquad (6)$$

Winning output neuron is decided by

$$\min \{ d_{ij,t}^2 \} \ for\ j = 1, 2, \dots n \ \ and\ \ i = 1, 2, \dots c \qquad (7)$$

Step3. Weight Updation: The weight of the winner neuron is updated by

$$\gamma_{i,t} = \gamma_{i,t-1} + \beta_{ij,t} \left(I_{fu,j} - \gamma_{i,t-1} \right) \qquad (8)$$

where $\beta_{ij,t}$ is learning rate.

Step4. If $\left\| \gamma_{i,t} - \gamma_{i,t-1} \right\| > \varepsilon$ set t = t + 1, update learning rate and go to step 2 else stop.

D. Change Map

Two cluster centers, γ_1 and γ_2 are obtained by applying KCN denoted by γ_{w_c} and γ_{w_u} for clusters w_c and w_u representing changed and unchanged clusters respectively. Each pixel of the fused image I_{fu} is assigned to one of the two clusters formed using eq. (9) . Based on the distance of each pixel from the cluster center, the pixels are assigned to the cluster having minimum distance. Final binary change map is created as

$$cm(x, y) = \begin{cases} 1, & \| I_{fu}(x, y) - \gamma_{w_c} \| \le \| I_{fu}(x, y) - \gamma_{w_u} \| \\ 0, & otherwise \end{cases} \qquad (9)$$

‖ ‖ is the Euclidean distance. The image consists of zeros and ones indicating “unchanged” and “changed areas” respectively.

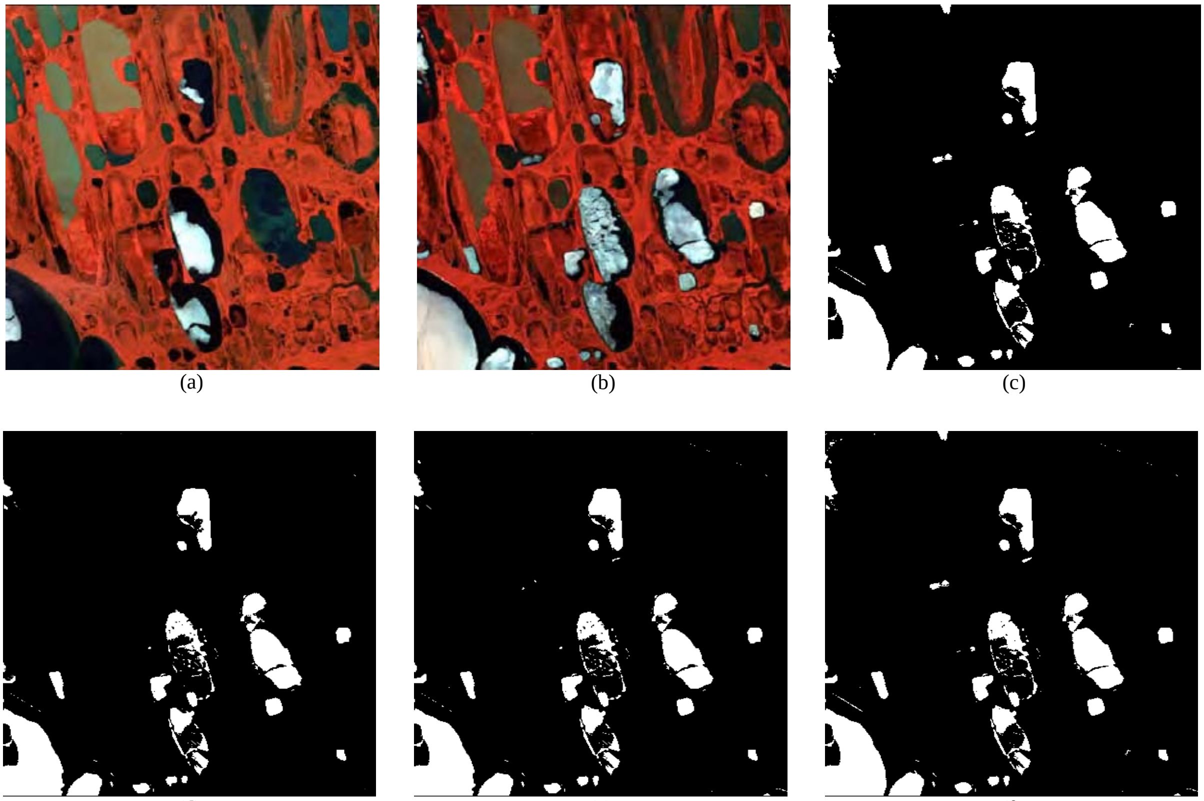
III. EXPERIMENTAL RESULTS AND DISCUSSION

The data set is taken from [16]. It consists of optical images of part of Alaska of size 1305× 1520 pixels. These were acquired on July 22, 1985 and July 13, 2005 by Landsat 5 TM consisting of seven bands. The specifications of Landsat 5 TM are shown in table I.The false color composite of the two images are shown in Fig.4(a) and Fig.4(b). The method was implemented in MatlabR2009a.

Table I
Specifications of Landsat 5 TM sensor.

Band	Wavelength Interval	Resolution
Band 1	0.45-0.52 μm	30m
Band 2	0.52-0.60 μm	30m
Band 3	0.63-0.69 μm	30m
Band 4	0.76-0.90 μm	30m
Band 5	1.55-1.75 μm	30m
Band 6	10.40-12.50 μm	120m
Band 7	2.08-2.35 μm	30m

The performance of the method was analyzed both qualitatively as well as quantatively. The results obtained from the proposed method were compared with two other methods i.e., PCA-based approach [7] and NSCT [10] method. The qualitative results of the various methods are shown in Fig. 4(d)-(f).It is observed that the result obtained from the proposed method shown in Fig.4 (f) is better than the other two method shown in Fig. 4(d) and Fig. 4(e).



(a) (b) (c)

(d) (e) (f)

Fig.4 Change detection results obtained from different methods (a) Landsat 5 Image acquired on July 22, 1985 (b) Landsat 5 Image acquired on July 13, 2005 (c) Ground truth of change detection (d) PCA-based approach (e)NSCT method (f) Proposed Method

For the quantitative assessment the following quantities have been computed for each change map.

TP (True Positive), the number of changed pixels correctly identified.

TN (True Negative), the number of pixels correctly identified as unchanged.

FN (False Negative), the number of changed pixels wrongly identified as unchanged pixels;

FP (False Positive), the number of unchanged pixels identified as changed pixels;

Several metrics can be derived from the above quantities to assess the performance of an algorithm [17]. In this paper, the following metrics are adopted:

1) Omission error (OE), indicates the probability that a changed pixel is wrongly identified as unchanged pixels; OE = FN/(FN + TP)
2) Commission error (CE), indicates the probability that a unchanged pixel is wrongly identified as a changed pixel; CE = FP/(TN + FP)

3) Percentage correct classification(PCC) is an indication of the overall accuracy of the algorithm in identifying change pixels as changed and unchanged pixels as unchanged;

$$PCC = (TP+TN)/(TP+TN+ FP+FN)$$

TABLE II
RESULT OF VARIOUS PARAMETERS USED FOR QUANTITATIVE COMPARISON

Method	TP	TN	FP	FN	OE (%)	CE (%)	PCC (%)
PCA-based approach	14796	162735	203	1134	7.12	0.12	99.25
NSCT	15096	162744	194	834	5.23	0.12	99.42
PA	15792	162828	110	138	0.86	0.06	99.86

The quantitative analysis of the various methods is shown in table II. It can be seen that the proposed method achieves highest PCC amongst all the methods. The OE of the proposed method is 0.86 while the OE for the other two methods is 7.12 and 5.23 indicating that the proposed method identifies the changed pixels most accurately. The CE of the proposed is also lowest which implies that the proposed method has minimum number of misclassifications.

IV. CONCLUSION

An unsupervised change detection method based on wavelet fusion and Kohonen clustering network is presented. The absolute difference and CVA image are fused using wavelet fusion rules to obtain a difference image in which changed areas are highlighted. The difference image is clustered into changed and unchanged areas using KCN. The results were compared with two other methods available in literature. The Percentage correct classification of the proposed method is higher than the other two methods while the commission and omission error is lesser than the other methods. Thus, the results obtained from the proposed method are quite satisfactory.

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