CHANGE DETECTION FROM REMOTELY SENSED IMAGES USING FUZZY DISTANCE MEASURE

[1]R.Kanaga Rathnam, [2] S. Kalaiselvi, [3]Dr.V.Gomathi, [4]Dr.K.G. Srinivasagan

[1] PG-Scholar, [2] Assistant Professor / CSE-PG, [3] Associate Professor (SG)/CSE,

[4]Professor and Head/CSE-PG,

National Engineering College (Autonomous) Kovilpatti, (India)

ABSTRACT

Automatic change detection is necessary for the remote sensing based applications. Change Detection (CD) is the process that identifies the changes occurred between two or more images based on the image properties. In case like disaster management, the fast and accurate detection of affected regions in images acquired at two different time instances that is before and after the disaster plays a vital role in taking appropriate decision. Hence, unsupervised change detection with no manual interventions in a reasonable time is very essential. Thus a hierarchical scheme is adapted, to identify the changed classes in different spectral behaviors. Fuzzy based clustering technique is employed on the Multitemporal images to segment the difference image into changed, unchanged and uncertain regions as well.

Keywords: Change Detection (CD), Multispectral (MS), Spectral Change Vector (SCV), Discrete Wavelet Transform (DWT)

I. INTRODUCTION

The surrounding world can be perceived through five senses. Some senses (touch and taste) require contact of sensing organs with the objects. However, much information about surrounding are required through the senses of sight and hearing which do not require close contact between the sensing organs and the external objects. Generally, Remote Sensing refers to the activities of recording / observing / perceiving (sensing) objects or events at far away (remote) places. The human visual system is an example of a remote sensing system in this general sense. Change Detection (CD) is the process that identifies changes occurred between two or more images based on the image properties [1].

The variation of image properties (e.g., pixel radiance value, texture, and shape) can be related to changes on the ground at different satellite observation times. Automatic change detection techniques have been widely used for remote sensing applications (e.g., ecosystem monitoring, urban area study, and disaster monitoring) [2]. Nevertheless, in order to effectively perform CD and obtain highly accurate results, it is important to devise advanced CD techniques that can automatically identify changes from multi-temporal images acquired by the new generation of remote sensing satellite systems.

For decades, images acquired by multispectral (MS) medium-resolution sensors have been a stable and popular data source in remote sensing CD. The EO satellite used to acquire images with much higher spatial and spectral resolutions.

II. RELATED WORKS

Ashish Ghosh et al, (2013) proposed a spatiocontextual unsupervised change detection technique for multitemporal, multispectral remote sensing images. He is employed in Badri *et al*, (2014) to perform the unsupervised change detection. The technique uses a Gibb's Markov Random Field (GMRF) to model the spatial regularity between the neighboring pixels of the multitemporal difference image. GMRF is a spatio-contextual statistical model mainly used for partitioning an image into a number of regions with the constraint of Gibb's distribution as prior probability distribution. Maximum a posteriori probability (MAP) is used to solve the change detection problem and MAP is estimated by using Hopfield type neural network. Hopfield's network consists of a set of neurons or nodes. The output of each neuron or node is given as input to other neurons; a single neuron is assigned to each pixel of the difference image and is assumed to be connected only to its neighbor. EM algorithm is used to estimate the GMRF model parameters.

Jin Zheng et al, (2013) discussed change detection in multitemporal synthetic aperture radar (SAR) images based on radon transform and Jeffery divergence. In this approach the local statistics in a sliding window are compared. In each analysis window, the image is projected onto two vectors in two independent dimensions. Kullback-Leibler (KL) divergence, called Jeffery divergence used to measure the distance between the two pairs of projections. The change map is produced by comparing the probability density functions (pdf) of the projections that are generated by Radon transform. Radon transform makes the speckle noise weak and shortens the tail. The main advantages of this approach is, the projection-based statistical model is closer to Gaussian pdf and improves the Edgeworth approximation of probability density function.

Sicong et al, (2015) proposed a hierarchical scheme is developed by considering spectral change classes having discriminable spectral behaviors. The hierarchical CD approach is used to identify all the possible changes presented between the considered images. The main contributions of this work are as follows: 1) Analysis and definition of the concept of changes in HS images, proposal of a technique for addressing the challenging multiple-change detection problem in HS images, by considering the difference of spectral change behaviors in the SCV domain at different spectral detail scales; and 2) proposal of an approach that models the detection of multiple changes in a hierarchical way, to identify the change information and separate different kinds of changes (major change, subtle change and finally change endmembers) according to their spectral difference. A minor limitation of this proposed method consists in the use of CVA for the pseudo binary CD step. By computing the magnitude of SCVs, small portions of the change information might be lost after compression, thus causing missed alarms in the final CD map. Although a proper setting of margin □ may limit this problem, the high dimensionality of HS data may still produce errors. Another issue to consider is the tuning of the threshold value (i.e., T□), which impacts on the final number of the output change endmembers. T□ should be fixed in order to tune the sensitivity of the method according to the end-user requirements.

Yaoguo et al, (2014) discussed unsupervised approach based on the combined difference image and k-means clustering for synthetic aperture radar (SAR). The first step of this method is speckle noise reduction. In this step the probabilistic-patch-based algorithm is used for speckle noise reduction. The subtraction operator and the log ratio operator is used for generate a difference image. The mean filter and the median filter are used to generate a two change maps. The mean filter focuses on making the change map smooth and the local area consistent. Median filter is used to preserve the edge information. K-means clustering algorithm is used to partition the difference image into two clusters.

Yuan et al, (2014) discussed semi-supervised distance method for multi-temporal hyperspectral images. First, Laplacian regularized metric learning algorithm is used to combine the large unlabeled information into learning framework. Second, distance metric is learned to detect change information. Third, learn a distance metric for detecting the change information under both “ideal” and “noisy” conditions. SSDM-CD is demonstrated to be an effective change detection method for complex Hyper spectral images. The final result was obtained based on threshold and the SVM.

Zhun-ga et al, (2014) proposed a multidimensional evidential reasoning (MDER) approach to estimate change detection from the fusion of heterogeneous remote sensing images. MDER is designed for the fusion of multisource classified images using same or distinct frames of discernment depending on the classifications done on the images. Two kinds of rules of combination are proposed for working either with free model, or with constrained model depending on the integrity constraints. The free model is well adapted when no prior knowledge is known on elements of the frame. The constrained model can be used if some integrity constraints between elements of the frame are known. The multidimensional elements in MDER could well represent the joint states of different images, which was useful for change detection. Belief functions C-means (BFCM) is applied to classify the pixel value of each pixel of the images.

III. METHODOLOGY

Change Detection (CD) is the process that identifies changes occurred between two or more images based on the image properties. The variation of image properties based on the pixel radiance value, texture and shape can be related to changes on the ground at different satellite observation times. Automatic change-detection techniques have been widely used for remote sensing applications such as ecosystem monitoring, urban area study, disaster monitoring. Nevertheless, in order to effectively perform change detection and obtain highly accurate results, it is important to devise advanced CD techniques that can automatically identify changes from multitemporal images acquired by the new generation of remote sensing satellite systems.

A novel hierarchical CD method for detecting changes in an images and separating them into different change end members. The proposed method mainly consists of four steps: a) Change vector analysis b) Pseudo-binary change detection to initialize the process and extract general changes; c) Change endmember detection based on DWT; d) Generation of the CD map by merging endmember clusters. The proposed phase architecture shows in below Fig.1.

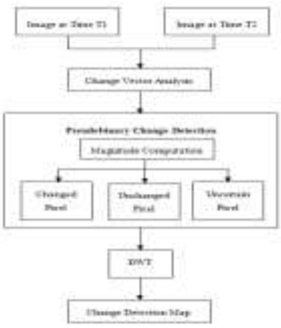

Figure 1 Block Scheme of the Proposed CD Approach For Multitemporal Images

- *Image Registration*

It is the process of properly aligning two images into a general co-ordinate system, in order to detect changes between the two images. Initially Images are segmented to regions based on Fuzzy C-means clustering approach which produces clusters.

3.1 Change Vector Analysis

Change vector analysis (CVA) method is used to produce the change detection in terms of magnitude and direction of the images. It uses two spectral channels to map both the magnitude of change and the direction of change between the two (spectral) input vectors. The change detection problem is initially formulated by considering two images, X_1 and X_2 with size $P\times Q$, acquired on the same geographical area at times t_1 and t_2, respectively. The differences between the two images (X_D) computed by subtracting multitemporal images from each other pixel by pixel.

$$X_D = X_2 - X_1 \qquad (1)$$

Let $\boldsymbol{x_i}$ be a Spectral Change Vector (SCV) with spatial position i (i =1,…, $P\times Q$) in $\boldsymbol{X_D}$, $\boldsymbol{x_i}$□$\boldsymbol{X_D}$. In such image each pixel is characterized by a SCV that shows as many elements as the spectral channels in the original images. Each element values that depend on change occurred between a specific wavelength and on the kind of change or not.

3.2 Pseudobinary Change Detection

This step is based on the analysis of the magnitude of SCVs according to traditional binary CD techniques. However it is referred as pseudo-binary because the output has three classes. After separating the change and no-change classes the uncertainty buffer class is defined. The class of changes is used to initialize the root node of a tree structure for change representation.

From $\boldsymbol{X_D}$ the magnitude and the direction of SCVs can be extracted. The first step of proposed method is based on distinguishing changed class from unchanged class. Thus only the magnitude □ □ is considered:

$$\rho = \sqrt{\sum_{b=1}^{B} (X_D^b)^2} \qquad (2)$$

where B denotes the number of spectral channels of the HS images, and X_D^b is the bth spectral difference in X_D. Thus, the whole binary change information is compressed into a 1 dimensional feature. Changed and unchanged pixels are separated into two groups according to a threshold value T□ computed on the magnitude variable. Change and no-change classes are assumed to be distributed and multiple changes are approximated as one single change class. The magnitude domain to focus only on the general change information.

In order to reduce the effect of possible thresholding errors and obtain conservative results that do not propagate significant errors in the next steps, a margin □ is set on the threshold computed on the histogram h(□) of the magnitude □ □ □ in Fig. 2) and three classes are defined. The three classes are as follows,

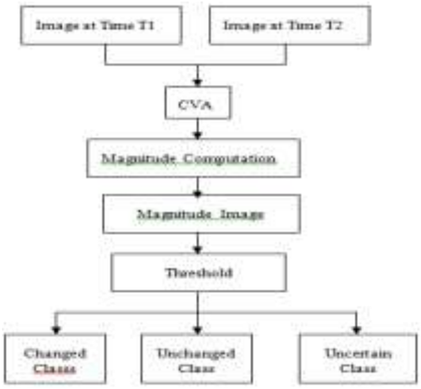

Figure 2 Block scheme of Pseudo-binary CD Map

1) *Class of uncertain pixels* (Ω_U), on which it is not possible to take a reliable decision at this level of the processing. These pixels will be analyzed and reclassified according to the generated endmembers;
2) *Class of changed pixels* (Ω_C), which includes pixels having a high probability to be changed, but without any information on their kind.
3) *Class of no-changed pixels* (ω_n), which only contains pixels having a high probability to be unchanged. These pixels are treated as a pure no-change class endmember due to their low magnitude.

Thus for a given SCV $\boldsymbol{x_i}$ in $\boldsymbol{X_D}$, a label is assigned according to the following rule:

$$x_i = \begin{cases} \Omega_c & \text{if } \rho_i \geq T_\rho \\ \Omega_u & \text{if } T_\rho - \delta \leq \rho_i < T_\rho \\ \omega_n & \text{if } \rho_i < T_\rho - \delta \end{cases} \quad (3)$$

where ρ_i is the SCV magnitude of the considered $\boldsymbol{x_i}$. Figure 2 illustrates the flowchart of the pseudo-binary CD step.

3.3 Change Endmember detection based on DWT

The Haar wavelet represents image in terms of positions of and magnitudes of maxima of the outputs of edge-sensitive filters. The Haar wavelet operates on data by calculating the sums and differences of adjacent elements. The first step of Haar wavelet is adjacent horizontal elements and then on adjacent vertical elements. The Haar wavelet's mother wavelet function ψ (t) can be described as:

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2} \\ -1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{other wise,} \end{cases} \quad (4)$$

Formula and its scaling function Φ (t) can be described as:

$$\Phi(t) = \begin{cases} 0 & 0 \leq t < 1 \\ 1 & \text{otherwise} \end{cases} \quad (5)$$

Measurements of actual physical phenomena may demand great quantities of computing resources. Therefore, often a finite number of values (a sample) are collected in Fig.3.

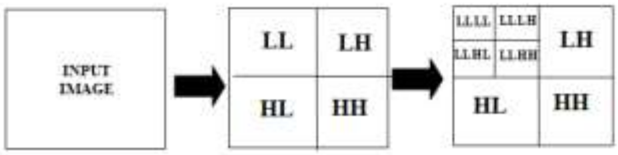

Figure 3: Decomposition hierarchy for 2-D DWT

Analysis-synthesis filter are often implemented with hierarchical sub-sampling, leading to a pyramid. Wavelets and quadrature mirror filters (QMFs) are often used this way, in which case they yield orthogonal transforms. The Haar filters are not very frequency selective, and so don't cleanly separate the information in the sub-bands.

IV. EXPERIMENTAL RESULTS

For evaluating the proposed work, in Fig. 4, the input images of two different time periods taken in the place of city of Trento (Italy) on July 2005, and October 2006 are considered.

Figure 4 Multitemporal Images Relating To The City of Trento

(a) Image Acquired In July 2005 (b) Image Acquired In October 2006

The first step of proposed method is change vector analysis. The difference image X_D can be computed pixelwise as the absolute-valued difference of intensity values of the two images under comparison. From the difference image the magnitude can be extracted and the magnitude image is obtained based on the histogram of the magnitude. The resultant magnitude image is presented in Fig. 5.

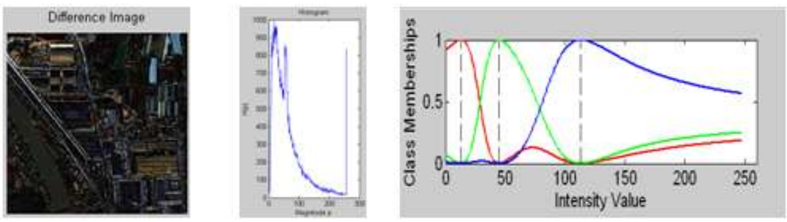

Figure 5 (a) Difference Image (b) Histogram of Magnitude (c) Intensity Value

The resultant classes of uncertainty pixels, changed pixels, and unchanged pixels of the input (change vector) image are presented in Fig.6.

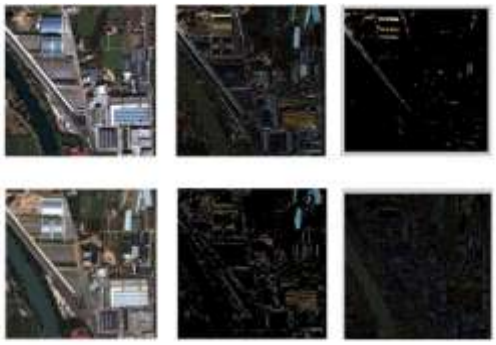

Figure 6 (a) Multitemporal Images (b) Input Image, Uncertain Pixel (c) Changed Pixel, Unchanged Pixel

The resultant classes of uncertainty pixels, changed pixels, and unchanged pixels of the input (change vector) image using Fuzzy Clustering is represented in Fig.7.

Figure 7 (a) Fuzzy Clustering (b) Unchanged Pixel (c)Uncertain Pixel (d) Changed Pixel

The resultant classes of first level decomposition and second level decomposition of the discrete wavelet transform using haar is represented in Fig.8 and Fig.9.

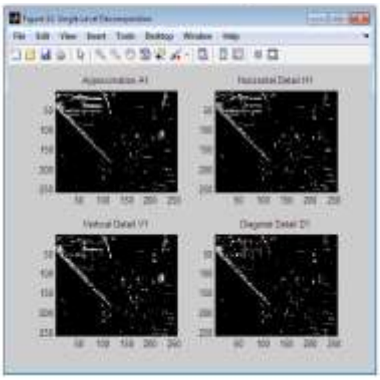

Figure 8 First Level Decomposition

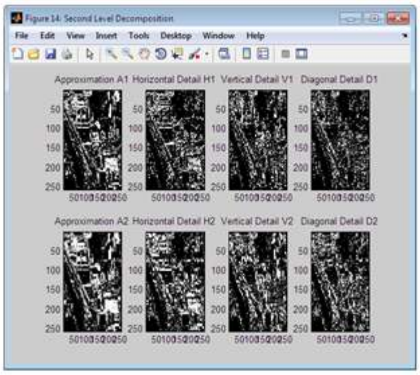

Figure 9 Second Level Decomposition

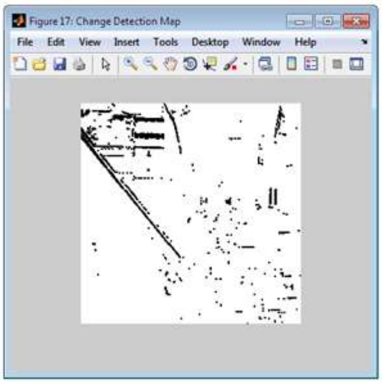

Figure 10 Change Detection Map

The final change detection map obtained by the proposed technique is represented in Fig.10.

V. CONCLUSION

In this paper, an unsupervised change detection method is proposed and implemented in land use and land cover images. The core idea of the system is to identify the changes between the temporal images. In the image obtained from the change vector, features such as changed pixels, unchanged pixels and uncertainty pixels are extracted. Finally, the change detection map will be produced by comparing the changed pixels and uncertainty pixels.

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