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Soft Computing Technique and PCA Based Unsupervised Change Detection Method in Multitemporal SAR Images

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ABSTRACT

In order to get the change detection image. An unsupervised change detection algorithm context-sensitive technique multitemporal remote sensing images. Change detection analyze means that according to observations made in different times, the process of defining the change detection occurring in nature or in the state of any objects or the ability of defining the quantity of temporal effects by using multitemporal data sets. There are lots of change detection techniques met in literature. It is possible to group these techniques under two main topics as supervised and unsupervised change detection. While that process is being made, image differencing method is going to be applied to the images by following the procedure of image enhancement. After that, the method of Principal Component Analysis is going to be applied to the difference image obtained. To determine the areas that have and don't have changes, the image is grouped as two parts by Fuzzy C-Means Clustering method. For achieving these processes, firstly the process of image to image registration is completed. As a result of this, the images are being referred to each other. After that, gray scale difference image obtained is partitioned into 3x3 non overlapping blocks. With the method of principal component analysis, eigenvector space is gained and from here, principal components are reached. Finally, feature vector space consisting principal component is partitioned into two clusters using Fuzzy C-Means Clustering and after that change detection process has been done

Keywords : Remote sensing, Change detection, Multi-temporal images, K-means

I. INTRODUCTION

In remote sensing, change detection aims to identify changes occurred on the Eart surface by analysing multitemporal images acquired on the same geographical area at different times (Coppin et al. 2004, Lu et al. 2004, Radke et al. 2005, Bruzzone and Bovolo 2013). Over the past few years, many change detection methods have beenimposed for various remotely sensed data. Generally, these methods can be grouped into supervised (post-classification) and unsupervised types (Bruzzone and Prieto 2000,Yetgin 2012). Though the supervised change detection methods supply the land-cover transformation, unsupervised change detection methods are more widely used and researched, thanks to the limitations of classification accuracy and ground reference absence (Bruzzone and Prieto 2000, Bovolo et al. 2008).

In this paper, we focus on the unsupervised change detection. Unsupervised change detection could be seen as a clustering process to partition pixels into changed and unchanged parts using some methods, such as image differencing, image ratio, image regression, and change vector analysis (CVA), etc. (Yetgin 2012, Shi and Hao 2013).Oneof the most widely used change techniques is to analyse the difference image created by subtracting corresponding bands of the multitemporal images pixel by pixel. Some literatures proposed automatic analysis for the difference image instead of an empirical threshold to identify changes (Huang and Wang 1995, Bruzzone and Prieto 2000, Baziet al. 2005, Imet al. 2008). Additionally some methods of pattern recognition or machine learning have also been applied to this issue like active contour model (Bazi et al. 2010), support vector machine (SVM) (Bovolo et al. 2008), wavelet transform (Bovolo and Bruzzone 2005, Celik and Ma 2010), fuzzy c-means (FCM) (Ghosh et al. 2011), and so on. Indeed, when FCM is used to detect changes, it is unreasonable to identify changes just using membership probability since the ranges of pixel values of the difference image belonging to the two clusters (changed and unchanged) generally have overlap (Ghosh et al. 2011). To reduce speckle noise of the change map, the spatial context information has also been utilized, for example,Markov randomfield (K-MEANS) is a classic approach to exploit the context information (Bruzzone and Prieto 2000, Melgani and Bazi 2006, Liu et al. 2008, Moser and Serpico 2009, Marchesi et al. 2010, Wang et al. 2013). Though K-MEANS is commonly robust in its change detection (or classification) performance, the resulting change map will eventually reveal an over-smooth result (i.e., loss of significant details and generating too large patches) without well defining for the boundary pixels (Wang and Wang 2004, Tso and Olsen 2005). In this paper, a novel change detection approach is proposed using FCM and K-MEANS to address, for example, the absence of detailed information of traditional K-MEANS and the value overlap of changed and unchanged pixels in the difference image of FMC. As shown in figure 1, the proposed approach is made up of three blocks as follows. First, the difference image is generated using CVA method based on multitemporal remotely sensed images. Then FCM is performed to the difference image, so the initial change map and the cluster membership probability of pixels belonging to changed and unchanged parts are obtained. Finally, the membership probability is introduced into K-MEANS using the spatial attraction model to control the boundary pixels in this process and the change map is produced.

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: 1) *image differencing*; 2) *normalized difference vegetation index*; 3) *change vector analysis*; 4) *principal component analysis (PCA)*; and 5) *image rationing*

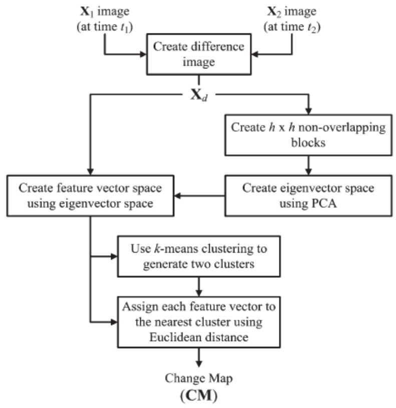

Figure 1. General scheme of the proposed approach

Simple Differencing

In this technique, spatially registered images of time I, and 1, are subtracted, pixel by pixel, to produce a further image which represents the change between the two times. Mathematically

$$Dx_{ij}^{k}(t_2) = x_{ij}^{k}(t_2) - x_{ij}^{k}(t_1) + C$$

Where =pixel value for band k and i and j are line and pixel numbers in the image, t1, =first date, t2r, =second date and C=a constant to produce positive digital numbers. The input data can be comprised of raw images or spatially filtered ones. Procedure yields a difference distribution for each band .

Image Ratioing

Ratioing is considered to be a relatively rapid means of identifying areas of change (Howarth and Wickware 1981, Howarth and Boasson 1983, Nelson 1983, Todd 1977, Wilson et al. 1976). In ratioing two registered images from different dates with one or more bands in an image are ratioed, band by band. The data are compared on a pixel by pixel basis. One computes

$$\mathrm{R}x_{\mathrm{ij}}^{\mathbf{k}}(\mathrm{t}_2) = x_{ij}^{k}(t_1) / x_{ij}^{k}(t_2)$$

Where $x_{ij}^{k}(t_2)$, is the pixel value of band k for pixel x at row i and column j at time t2. If the intensity of reflected energy is nearly the same in each image then $\mathrm{R}x_{ij}^{k}(t_2)$, this indicates no change.

Principal Components Analysis (PCA)

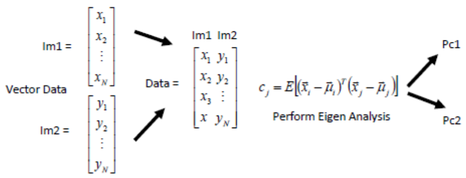

Figure 2. PCA algorithm for change detection

Principal Component Analysis is a linear transformation technique and probably the most common of these techniques. The main principal of the PCA approach is to use as input a set of images and to reorganize them via a linear transformation, such that the output images are linearly independent. The new coordinate system for the data is projected such that the greatest variance lies on the first axis or the first principal component and the second greatest variance on the second axis. This technique is usually used to reduce the number of spectral bands or in compression schemes. In CD studies, the consequence of this linearization is that unchanged pixels or common information shared by a pair of images are 21 expected to lie in a narrow elongated cluster along a principal axis equivalent to the first component (PC1). On the contrary, pixels containing a change would be more unique in their spectral appearance and would be expected to lie far away from this axis (PC2).

K-means Clustering

The K-means clustering is a simple clustering method which uses iterative technique to partition *n* observation into *k* clusters. The partition of *n* observation into *k* clusters is based on the nearest mean principle. Even though it is fast and simple in execution, the clustering will not converge if the selection of initial cluster center is not made properly. K-means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. [Dalmiya et.al, 2012].

The basic *k*- means clustering algorithm is as follows:

*Step 1 : Choose **k** = # of clusters.*

*Step 2 : Pick **k** data points randomly from the dataset. These data points act as the initial cluster centers*

*Step 3 : Assign each data point from the **n** observation into a cluster with the minimum distance between the data point and cluster centre.*

Step 4 : Re-compute the cluster centre by averaging all of the data points in the cluster.

Step 5 : Repeat step 3 and step 4 until there is no change in cluster centers

Therefore K-means clustering, the key endeavor is to partitions the *n* observation into k sets (k<n) s={s1,s2,s3,…..sk} so as to minimize the within cluster sum of squares.

$$\arg\min \sum_{i=1}^{K} \cdot \sum_{x_j \in s_i} \| x_j - u_i \|^2$$

Where *ui* is the mean of points in *Si*, *K* is the number of clusters and *x*j is the j^{th} data point in the observations [Ramani et.al, 2013][Gumaei et.al,2012].

Fuzzy C-means clustering

The Fuzzy C-means (FCM) algorithm is a method of clustering which allows one of the *n* observations belongs to two or more clusters. It is a frequently used method in pattern recognition [Thangavel and Mohideen, 2010]. It is based on the minimization of the following objective function to achieve a good classification.

$$v_{ij} = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_{kj}}{\sum_{k=1}^{n} (\mu_{ij})^m} \qquad (1)$$

2) *Calculate the distance matrix $D_{[c,n]}$.*

$$D_{ij} = \left(\sum_{j=1}^{m} (x_{kj} - v_{ij})^2 \right)^{1/2} \qquad (2)$$

3) *Update the partition matrix for the r^{th} step, $U^{(R)}$ as*

$$\mu_{ij}^{r-1} = \left(1 \Big/ \sum_{j=1}^{c} (d_{ik}^{r} / d_{jk}^{r})^{2/m-1} \right) \qquad (3)$$

Where *m* is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster *j*, *xi* is the i^{th} of the d-dimensional measured data, *cj* is the d-dimensional center of the cluster and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of member ship uij in equation and the cluster centers Cj by equation

II. CONCLUSION

An unsupervised change detection technique is developed byconducting *fcm* means clustering on feature vectors which are extracted using $h \times h$ local data projection onto eigenvector space. The eigenvector space is generated using PCA on $h \times h$ nonoverlapping difference image blocks. The proposed method uses $h \times h$ neighborhood to extract feature vector for each pixel so that it automatically considers the contextual information.The proposed algorithm is simple in computation yet effective in identifying meaningful changes which makes it suitable for real-time applications. It produces results comparable, even better, with the MRF-based approach [5], which requires computationallyexpensive data modeling and parameter estimation.Simulation results show that the proposed algorithm performs quite well on combating both the zero-mean Gaussian noise and the speckle noise, which is quite attractive for change detection in optical and SAR images

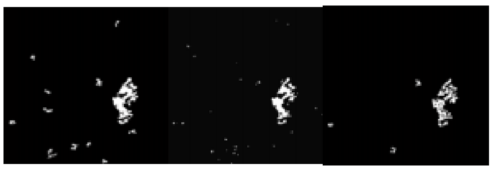

Figure 3. Change detection results obtained by using Kernel FCM-means clustering

Table 2.Change Detection Results Obtained By Using Kernel K-means Clustering on the Difference Images.

Difference Image	Accuracy
Mean-Ratio	89.999
Log-ratio	92.542
Fused Image	94.357

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