AN UNSUPERVISED CHANGE DETECTION ALGORITHM BASED ON SPECTRAL SIGNATURE ANALYSIS IN MULTISPECTRAL IMAGES

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ABSTRACT

In this work an innovative unsupervised change detection technique for multispectral and hyperspectral images is proposed. It consists in the comparison between two co-registered and radiometrically correct multispectral images, carried out by comparing pixels’ spectral signatures. Supposing a change is occurred, we can state that the spectral vector associated to a pixel in the “changed image” makes an angle with the spectral vector of the corresponding pixel in the reference image or has a different norm. Hence in our approach we have used for the classification of changed areas two main features based on the direct or indirect measure of the angle and of the norm of changed vector projection on the corresponding spectral vector in the reference image. More in deep, since cosine and sine functions represent an indirect measure of this angle, we can calculate these values to obtain the changes we are looking for. Nevertheless, measuring an angle that is equal to zero doesn’t mean that no change has occurred, because there might have been just a variation along the reference spectral vector’s direction that has no effect on angle but only on pixel brightness. So we have defined another change indicator, the Brightness Change Factor, whose value gives us the information about changes occurred in pixels’ radiance values.

1. INTRODUCTION

In the last decades change detection represented one of the main topics attracting Remote Sensing community interest. Change analysis is in essence a spatial comparison of two or more land covers of the same geographical area produced from remotely sensed data that are recorded at different times [1]. In literature a number of techniques have been presented, applied and evaluated; we can divide them into two general classes [2]; (1) post-classification comparison and (2) those based on direct approach (pre-classification). Among the latter approaches we can find Image Simple Differencing [3]-[5], Image Ratioing [5], Principal Component Analysis (PCA), Change Vector Analysis (CVA) [6]-[14]. CVA technique is the most used to detect changes in multispectral and hyperspectral images, because it takes into account the informational content of each spectral band. CVA is a multivariate technique, which accepts as input N bands, transforms or spectral features from each scene pair [8]. For each scene pair, these bands comprise the axes of an N-dimensional space. In [12] the CVA is applied only to Red and Near-InfraRed channels of Landsat TM sensor, in [15] is applied on NDVI and BI indexes, in [7] tasseled cap components are used and in [10] fraction images for soil, vegetation and shade are generated by the LSMM (Linear Spectral Mixture Model) from original images. The CVA algorithm produces two change information: multispectral change magnitude and change vector direction. To discriminate among all changes those more significant, vector’s magnitude is compared with a threshold value, so that only changes over the threshold represent the relevant ones. The threshold is usually chosen empirically, but in [13] an automatic method to determine threshold is presented.

In the following paper an innovative change detection approach is presented. It produces two change information, the angle between corresponding spectral vectors in two multispectral images, indicating a change occurred in pixel spectral signature, and the Brightness Change Factor, indicating a variation occurred only in pixel radiance value. These indicators are different from those produced by CVA technique, but they are extremely effective if used in the training process of a classification system.

2. PROPOSED APPROACH

2.1. Theoretical Background

Let us consider two N-dimensional arrays \( X = (X_1, X_2, ..., X_N) \) and \( Y = (Y_1, Y_2, ..., Y_N) \). Considering \( Y \) as the reference vector, we can express \( X \) as follows:

\[ X = P_Y(X)I_Y + P_{XY}(X)I_{XY} \]

where \( P_Y(X)I_Y \) is X projection along Y direction, while \( P_{XY}(X)I_{XY} \) is X projection on the orthogonal space to the previous direction. Considering the formulation of orthogonal projection, which involves the scalar product between two vectors, we can derive an expression for the cosine of the angle (\( \theta \)) made by \( X \) and \( Y \):

\[ \cos \theta = \frac{P_Y(X)}{\|X\|} \]

Cosine gives us a measure of how two vectors are similar, so that the higher the cosine value is the more similar the considered vectors are.

Let’s suppose \( X \) and \( Y \) are corresponding spectral vectors in two multispectral images acquired on the same area but at different times; we want to detect the changes occurred between these two dates. Supposing that there is no preferred change direction, the changed vector has in each direction the same energy, i.e. \( \frac{1}{N}E_{tot} \) if we are in a N-dimensional space and \( E_{tot} \) is the total energy of changed vector in this space. Therefore the orthogonal component of \( X \), i.e. \( P_Y(X)I_{XY} \), is characterized by a significant amount of energy, being its dimension equal to (N-1), so if a change has occurred we observe a certain angle between the corresponding spectral vectors of a given pixel in the two images. Measuring this angle we can obtain the change information, and cosine represents an indirect measure of this angle: the higher its value is, the lower magnitude of changes.
the corresponding angle value is so the less significant pixel change is. Nevertheless, if we observe an angle equal to zero we cannot state that no change has occurred, because there might have been a variation only in pixel brightness, that involves the reference direction, i.e. it has only the component along \( Y \) direction. To detect also this kind of change we have defined another change indicator, called \( \text{Brightness Change Factor} \), that is able to provide the information about pixel radianc e values modification. Expressing \( X \) as follows:

\[
X = Y + I
\]

where \( I \) represents the innovation that we can find in \( X \) compared to \( Y \). Therefore we can express the previous defined component as:

\[
P_Y(X)I_Y = Y + P_Y(I)I_Y
\]

\[
P_{LY}(X)I_{LY} = P_{LY}(I)I_{LY}
\]

So we can measure pixel’s intensity change by the ratio between the norms of \( P_Y(I)I_Y \) and \( Y \) itself, and we have expressed this ratio as follows:

\[
1 + BCF = \frac{\| P_Y(I)I_Y \|}{\| Y \|}
\]

where \( BCF \) is the \( \text{Brightness Change Factor} \). Significant changes are associated to \( BCF \) values that are far off zero, where zero represents the condition in which no change in pixel brightness has occurred.

2.2. Change Vector Analysis

CVA technique is an empirical method of detecting radiometric changes between multidate satellite images in any number of spectral bands. This method produces information about both the amount and the direction of changes in the data, so that the changes are characterized by vectors having magnitudes and directions in multispectral change space [9]. Let \( X_1 = (X_{11}, X_{12}, \ldots, X_{1N}) \) and \( X_2 = (X_{21}, X_{22}, \ldots, X_{2N}) \) be two multispectral images. The Change Vector can be expressed as:

\[
\Delta g = \begin{bmatrix}
X_{21} - X_{11} \\
X_{22} - X_{12} \\
\vdots \\
X_{2N} - X_{1N}
\end{bmatrix}
\]

where the magnitude can be calculated using the equation of the Euclidean Distance in an \( N \)-dimensional space:

\[
\| \Delta g \| = \sqrt{\sum_{k=1}^{N} (X_{2k} - X_{1k})^2}
\]

Change directions refer to the angle between the change vector and a reference direction, usually defined as the horizontal axis in a simple two dimensional feature space (figure 2.1c). Vector direction has an angle ranging from 0° to 360°. One approach of dealing with this continuous range is to divide it into sectors; presumably, each sector corresponds to a unique category of change, in addition to the quantitative magnitude of change. The conventional two-band change vector analysis can be extended to many dimensions via hyperspherical direction cosine change vector analysis: incorporation of multiple bands produces more accurate results than conventional change vector analysis. However, it is problematic to discriminate the nature of change from the derived distance if a large number of spectral bands is used [1].

2.3. Theoretical Comparison

Moreover we can compare the information produced by our algorithm with those provided by CVA technique, at least from a theoretical point of view. Both techniques allow us to obtain two informations, the one concerning magnitude and the other concerning an angle. Our cosine, therefore the associated angle, represents a measure of how pixel spectral signature has changed, instead the angle obtained by CVA technique locates change vector in the \( N \)-dimensional space but it has to be interpreted as a measure of change direction, that is the increase and/or decrease of some reference values, such as radiance values of original bands or indicators as NDVI or BI. So, to determine if a pixel spectral signature has changed by CVA direction we should have at our disposal some supplementary information about how the type of changes we are looking for are related to chosen reference values. For instance, in [12], Red and Near-InfraRed bands values are chosen as reference values, so they divide bi-dimensional space in four quadrants, assigning a particular type of change to each of them on the basis of spectral behavior of bands they consider. Though our algorithm doesn’t need a-priori information about possible change classes to establish if spectral signature has changed. With regard to magnitude, our \( BCF \) takes into account pixel intensity variation only along the reference direction, and it is because we introduced \( BCF \) just to detect those changes occurred along that direction, while the CVA magnitude represents the total intensity change occurred between considered multispectral images bands.

3. MATERIAL AND METHODS

3.1. Dataset description and pre-processing

The chosen dataset is made up of two multispectral co-registered images of Pavia city, in Italy, the one acquired in April 1994 by Landsat5 TM sensor, and the other acquired in October 2000 by
Landsat7 ETM+ sensor. Both images has a spatial resolution of 30x30 m. Because of the different sensors used they did not present the same radiometric characteristics, so we had to correct them radiometrically so that they presented the same mean value and the same standard deviation.

3.3. Results and Discussions

To calculate cosine and Brightness Change Factor we have built a C++ object oriented library, characterized by classes and functions conveniently defined. In figure 3.1 RGBs of the two images are shown, while in figure 3.2 results from cosine and BCF calculation are displayed. Finally figure 3.3 shows the main changes occurred visually identified.

First of all we note like cosine is able to detect significant changes occurred in pixel spectral signature, while BCF represents a complementary indicator because it is able to find those changes occurred only in pixel radiance value, those highlighted even by cosine but above all those which cosine is not able to detect.

4. CONCLUSIONS

In this paper we described an innovative unsupervised change detection method for multispectral and hyperspectral images, and we compared it to the most used change detection technique for this kind of images, i.e. Change Vector Analysis. Although both algorithms produces two informations about change, our technique is able to provide a direct measure of pixel spectral signature change without needing a priori information about possible types of change, such as CVA technique does.

8. REFERENCES