A NEARLY LOSSLESS 2D REPRESENTATION AND CHARACTERIZATION OF CHANGE INFORMATION IN MULTISPECTRAL IMAGES

Francesca BOVOLO, Silvia MARCHESI, Lorenzo BRUZZONE

Information Engineering and Computer Science Dept., University of Trento
Via Sommarive, 14, I-38123, Povo, Trento, Italy

1. INTRODUCTION

Several unsupervised change detection (CD) methods for multispectral images acquired by passive sensors have been proposed in the remote sensing literature [1],[2]. Among them, a widely used technique is the change vector analysis (CVA) [3],[4]. The CVA computes a *B*-dimensional (*B*D) difference image by subtracting the spectral feature vectors associated with each corresponding pixel in two images acquired on the same scene at two different times. In the resulting image each pixel is represented by a *B*D spectral change vector (SCV). As different kinds of changes on the ground have different effects on spectral channels, each dimension in the feature space defined by SCVs is potentially useful for solving the CD problem. The unsupervised solution of this complex *B*D problem implies the application of clustering algorithms to *B*D SCVs. Such kind of solutions lead often to poor CD accuracies. Moreover the *B*D ($B > 2$) space is difficult or impossible to visualize for applying semi-automated interactive data-analysis techniques. Therefore, the most common practice is to define alternative representations of the considered problem by mapping down the change information from a *B* onto a lower dimensional space. The most common and easiest approach is to reduce the *B*D problem to the 1D problem modeled by the magnitude of SCVs [3]. In this case a simple thresholding of the magnitude variable allows one to obtain the CD map. This approach allows one to classify only the presence/absence of changes [3],[4], and no information can be retrieved about different kinds of changes. In alternative, if some prior knowledge on the kind of changes occurred on the ground is available, it is possible to select the 2 bands most relevant to the considered CD problem [4]. The main advantage in this case is that the selected 2D problem is easy to visualize and manage. However, the most significant drawback is that the CD solution can be affected by the loss of information implicit in the band selection process.

According to this analysis, it emerges the need of defining a 2-dimensional feature space where the most of the information about different kinds of changes present in the original *B*D space is nearly-lossless compressed and can be easily plotted and extracted. In order to face the aforementioned problem, we propose a method for effectively compressing the *B*-dimensional change information in a 2D dimensional space without neglecting a priori any spectral channel and making it possible to easily display this information, as well as process it with interactive semi-automatic methods.

2. PROPOSED 2D REPRESENTATION OF THE CHANGE INFORMATION

Let us consider two coregistered multispectral images, $\mathbf{X}_1$ and $\mathbf{X}_2$ acquired over the same geographical area at different times t_1 and t_2, respectively. Let $\mathbf{X}_\mathrm{D}$ be the multispectral difference image obtained by subtracting the spectral feature vectors associated with each corresponding spatial position in the two considered images. Let $X_{b,\mathrm{D}}$ be the image representing the bth ($b = 1,\ldots,B$) component of the multispectral difference image $\mathbf{X}_\mathrm{D}$. Finally, let $\mathbf{\Omega}=\{\omega_n, \Omega_c\}$ be the set of classes of no-changed (ω_n) and changed (Ω_c) pixels to be identified. $\Omega_c = \{\omega_{c1}, \omega_{c2}, \ldots, \omega_{cK}\}$ is the set of K possible classes (kinds) of change occurred in the considered area.

Following the previous considerations, we propose to compress the information in $\mathbf{X}_\mathrm{D}$ into a 2D feature space according to a nearly lossless transformation. The two features define a framework in which the change information can effectively and intuitively be represented and extracted.

2.1. 2D nearly lossless representation

The first of the considered features is the well known (and widely used) magnitude ρ of SCVs in $\mathbf{X}_\mathrm{D}$ given by

$$\rho = \sqrt{\sum_{b=1}^{B} X_{n,\mathrm{D}}^2}, \quad \rho \in [0, \rho_{max}] \tag{1}$$

where ρ_{max} is the maximum value assumed by the magnitude for the considered dataset. This feature carries information about the presence/absence of changes [3],[4] and represents a valuable and robust tool for distinguishing changed from no-changed pixels [2],[4].

As the magnitude of SCVs does not include information about different kind of changes a complementary feature should be defined. This measure should effectively compress the information about different kinds of changes from B-1 dimensions to 1-dimension with the lowest possible loss of information. According to this observation, the second feature is the direction of SCVs computed in radians as

$$\vartheta = \arccos \frac{1}{\sqrt{B}} \left(\sum_{b=1}^{B} X_{b,\mathrm{D}} \Big/ \rho \right), \quad \vartheta \in [0, \pi) \tag{2}$$

ϑ is the angle computed between a BD SCV and a BD unit vector with elements all equal to $\sqrt{B}/B$ ..

The pair of features (ρ and ϑ) represents the nearly lossless compressed information on the changes occurred on the ground.

2.2. Characterization of the change information

Similarly to what presented in [3], the properties of the two features defined according to (1) and (2) can be exploited for defining a representation of the CD problem in a 2D feature space easy to visualize and manage.

The ranges of existence of ρ and ϑ bound the information present in $\mathbf{X}_\mathrm{D}$ within a Magnitude-Angle (*MA*) domain defined as

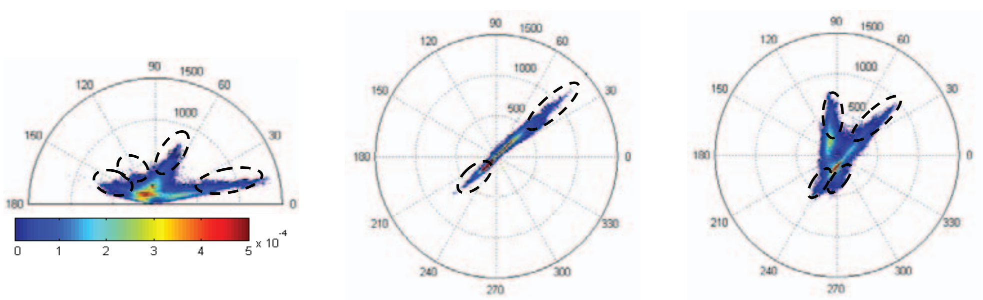
$$MA = \{\rho \in [0, \rho_{max}] \text{ and } \vartheta \in [0, \pi]\} \tag{3}$$

Eq. (3) represents a semi-circle that includes all SCVs of the considered data set. Within this domain, different regions of interest can be identified associated to: i) the class of no-changed pixels, and ii) the class of changed pixels. The latter region can be divided in further regions associated to different kind of changes. Analytical expressions for the statistical distribution of ρ and ϑ in the different regions of interest can be derived. For space constraints, further details on this aspect will be given in the full paper.

It is worth stressing that some ambiguity rises from the information compression process which is mainly due to the simplified representation of the angle variable. The loss of information may result in similar values of ϑ for different kinds of changes that therefore becomes undistinguishable. Nevertheless, the defined 2D feature space considers in the solution of the CD problem all available spectral bands, without requiring prior information about relevant spectral channels which is necessary for a 2D CVA in polar coordinates. This is a valuable advantage. Moreover, the low dimensionality makes it easy to visualize the problem for semi-automatic and interactive CD process.

3. EXPERIMENTAL RESULTS AND DISCUSSION

Several experiments were carried out on multispectral and multitemporal datasets. Here few results obtained for a very high geometrical resolution data set composed of two images acquired in October 2005 and July 2006 by the multispectral sensor mounted on the Quickbird satellite (4 spectral channels) of an area nearby the city of Trento (Italy) are reported. Between the two acquisition dates three different kinds of changes can be observed (i.e., K=3): (i) changes in the cover of both buildings and crop fields (ω_{c1}); (ii) seasonal changes in green areas (ω_{c2}); and (iii) changes along the river bank due to an increase of the water level (ω_{c3}).



(a) (b) (c)

Figure 1. Scatterograms in polar coordinates obtained by applying: (a) the proposed technique; (b) the polar CVA to spectral channels 2 and 3; and (c) the polar CVA to spectral channels 3 and 4.

Figure 1.a shows the scatterogram in 2D polar coordinates obtained applying the proposed 2D representation. This plot was compared with the scatterograms obtained by applying the CVA technique to: channels 2 and 3 (Figure 1.b); and channels 3 and 4 (Figure 1.c). In the first case the two spectral bands have been chosen

randomly within all possible combinations of 2D spectral channels, while in the second case they have been chosen according to some prior knowledge about changes occurred on the ground.

Observing the scatterogram in Figure 1.a, four main clusters (dashed circles) showing high ρ and four preferential values of ϑ can be easily identified: three are related to each one of the three different kinds of changes, while the fourth one is mainly related to the effects of registration noise (RN)[1].

The comparison among Figures 1.a, b and c points out that: i) when considering channels 2 and 3 only two clusters can be identified (dashed circles), one related to ω_{c1} , and one related to RN effects; ii) when considering channels 3 and 4 four clusters can be identified associated to the three different kind of changes and to RN (as for the proposed method). In other words if no prior information about changes is used for selecting spectral channels, it is likely to miss relevant information about some changes, whereas a proper selection of channels gives results similar to the ones achieved by the proposed method but without any prior information.

Further results will be documented in the full paper.

REFERENCES

[1] P. R. Coppin, I. Jonckheere, and K. Nachaerts, "Digital Change Detection Techniques," *Int. J. Rem. Sens.*, vol. 25, no. 9, pp. 1565-1596, 2004.

[2] A. J. Radke, S. Andra, O. Al-Kofahi, and B. Roysam, "Image Change Detection Algorithms: A Systematic Survey," *IEEE Trans. on Image Proc.*, vol. 14, no. 3, pp. 294-307, 2005.

[3] F. Bovolo and L. Bruzzone, "A Theoretical Framework for Unsupervised Change Detection Based on Change Vector Analysis in Polar Domain," *IEEE Trans. Geosci. and Rem. Sens.*, vol. 45, no. 1, pp. 218-236, 2007.

[4] L. Bruzzone and D. Fernández Prieto, "Automatic Analysis of the Difference Image for Unsupervised Change detection," *IEEE Trans. Geosci. Rem. Sens.*, vol. 38, no. 3, pp. 1170-1182, 2000.

[5] F. Bovolo, L. Bruzzone, and S. Marchesi, "Analysis and Adaptive Estimation of Registration Noise in VHR Images," *IEEE Trans. Geosci. Rem. Sens.*, vol. 47, no. 8, pp. 2658-2671, 2009.

[1] It is worth noting that RN in VHR images strongly affects the CD process, as it results in clusters with properties very similar to the ones of true changes. An analysis of RN is out of the purposes of this work, but the reader is referred to [5] for a detailed analysis on it.