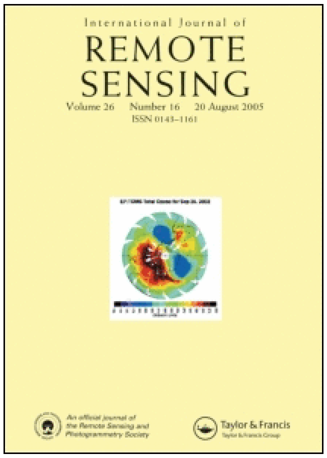

International Journal of Remote Sensing
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713722504

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Online Publication Date: 01 March 2000
To cite this Article: Bruzzone, L. and Prieto, D. Fernandez (2000) 'An adaptive parcel-based technique for unsupervised change detection', International Journal of Remote Sensing, 21:4, 817 - 822
To link to this article: DOI: 10.1080/014311600210614
URL: http://dx.doi.org/10.1080/014311600210614

INT. J. REMOTE SENSING, 2000, VOL. 21, NO. 4, 817–822

An adaptive parcel-based technique for unsupervised change detection

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(*Received 24 February 1999; in final form 22 June 1999*)

Abstract. A novel unsupervised technique for the detection of changes in multitemporal remote sensing images is presented. It adaptively exploits the spatial–contextual information contained in the neighbourhood of each pixel to reduce the effects of noise and hence to increase change-detection accuracy. In addition, the proposed definition of an adaptive pixel neighbourhood allows a precise location of the borders of changed areas.

1. Introduction

Unsupervised change-detection techniques generally identify changes by thresholding the image generated by differencing two co-registered remotely sensed images acquired in the same area at different times (Singh 1989, Fung 1990, Bruzzone and Serpico 1997a, b). However, as these techniques are applied at the pixel level, they are generally sensitive to noise that may affect individual pixels; this may result in low change-detection accuracies.

A reduction in the effects of noise can generally be obtained by using simple pre-processing or post-processing algorithms (Singh 1989), e.g. filtering algorithms can be applied to the original images, the difference image or the map of changes (Singh 1989, Richards 1993). Such algorithms typically involve using a pre-defined neighbourhood configuration that is equal for each pixel and do not take into account the homogeneity/heterogeneity of the particular neighbourhoods around pixels. This may lead to a poor reduction in noise and a rough location of the borders of changed areas.

In this letter, a change-detection technique based on an original definition of adaptive parcels, i.e. small homogeneous regions shared by both original images, is presented. The adaptive nature of parcels allows spatial–contextual information to be exploited so that noise may be reduced without damaging the boundaries of changed areas. In addition, the characterization of parcels with a set of different features permits the identification of changes involving variations in both the spectral and textural properties of land-covers.

2. The proposed definition of adaptive parcels

Let us consider two co-registered multispectral images, $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, acquired in the same area at two different times, t_1 and t_2. To simplify the notation, a single spectral band will be considered; the generalization of the technique to a multiband

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2000 Taylor & Francis Ltd
http://www.tandf.co.uk/journals/tf/01431161.html

case is straightforward. Let $x_1(m, n)$ and $x_2(m, n)$ denote the grey-level values of pixels with the coordinates (m, n) in $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, respectively.

We define a 'parcel' as an elementary homogeneous region common to both original images, $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$. Let $P(\boldsymbol{X}_1, \boldsymbol{X}_2) = \{p_1, p_2, \ldots, p_N\}$ be the set of parcels associated with the images $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, where $p_j = \{(e, f), (m, n), \ldots, (g, h)\}$ is the j-th parcel made up of M_j connected pixels. Let the uniformity predicate $\boldsymbol{U}(Z)$ (Fu and Mui 1981) assign the value *true* or *false* to the pixel subset Z, depending on the homogeneity properties of the grey-level values of all the pixels belonging to Z. According to our definition, $P(\boldsymbol{X}_1, \boldsymbol{X}_2)$ should satisfy the following conditions:

$$\bigcup_{j=1}^{N} X_1^j = \boldsymbol{X}_1 \quad \text{and} \quad \bigcup_{j=1}^{N} X_2^j = \boldsymbol{X}_2, \quad \text{where} \quad X_i^j = \{x_i(m, n), (m, n) \in p_j, i = 1, 2\} \tag{1}$$

$$\text{Pixels in } p_j \ (j = 1, 2, \ldots, N) \text{ are } \textit{connected} \tag{2}$$

$$\boldsymbol{U}(X_1^j) = \textit{true} \quad \textbf{AND} \quad \boldsymbol{U}(X_2^j) = \textit{true} \quad (j = 1, 2, \ldots., N) \tag{3}$$

$$\boldsymbol{U}(X_1^j \cup X_1^k) = \textit{false} \quad \textbf{OR} \quad \boldsymbol{U}(X_2^j \cup X_2^k) = \textit{false} \ \text{for } j \neq k, \text{ where } X_i^j \text{ and } X_i^k \ (i = 1, 2) \text{ are } \textit{adjacent} \tag{4}$$

Conditions (1) and (2) guarantee that all the pixels in the $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ are distributed into N connected regions. Condition (3) determines the homogeneity properties of the parcels in both original images, and condition (4) expresses the maximality (Fu and Mui 1981) of each parcel.

It is worth noting that, according to our definition, the uniformity predicate $\boldsymbol{U}(\cdot)$ has to be selected such that 'physical' regions in an image (e.g. a crop field) may be decomposed into a number of smaller homogeneous areas (i.e. 'parcels'). This requires that the predicate $\boldsymbol{U}(\cdot)$ be rather restrictive.

3. Change detection with adaptive parcels

The proposed technique is based on the reasonable assumption that the area of the changes to be detected is larger than the spatial resolution of the sensor used (otherwise the sensor is not suitable for the particular application considered). Under this assumption, generally adopted when spatial–contextual information is used, we propose to perform change detection at the parcel level, i.e. to make a direct comparison of corresponding parcels in the two original images. To this end, at each date, parcels are characterized by R-dimensional feature vectors, whose components are measures of the local properties of parcels (e.g. the mean value, texture characteristics). Therefore, as parcels are stable over time (i.e. they are homogeneous in both images), change detection is achieved by comparing the feature vectors of all the parcels in the two images.

The technique involves two main tasks: generation of the set of parcels $P(\boldsymbol{X}_1, \boldsymbol{X}_2)$; and generation of the parcel-based difference image and thresholding.

3.1. *Generation of the set of parcels $P(X_1, X_2)$*

The generation of parcels can be accomplished in two steps: (1) segmentation of the two original images and (2) fusion of the segmentation maps.

(1) Two segmentation maps, $S_1 = \{s_1^1, s_1^2, \ldots, s_1^{H_1}\}$ and $S_2 = \{s_2^1, s_2^2, \ldots, s_2^{H_2}\}$, composed of H_1 and H_2 regions, respectively, are produced by applying a segmentation algorithm separately to the two images $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ (a classical segmentation algorithm

can be used in this step) (Fu and Mui 1981). The segmentation process should be such that each region s_i^k satisfies the following conditions:

$$U(s_i^k) = true\ (k = 1, 2, \ldots, H_i;\ i = 1, 2) \tag{5}$$

$$U(s_i^j \cup s_i^k) = false \quad \text{for} \quad j \neq k \quad (i = 1, 2) \tag{6}$$

The parameters that control the uniformity predicate $U(\cdot)$ in the segmentation algorithm should be tuned so that under-segmentation errors may be avoided, that is, S_1 and S_2 should not contain heterogeneous regions composed of pixels associated with different physical areas. Therefore, as over-segmentation errors do not decrease the effectiveness of the proposed technique, the segmentation parameters should be selected such that the uniformity predicate $U(\cdot)$ will impose a high degree of homogeneity.

(2) The fusion process is carried out to generate the set of parcels $P(X_1, X_2) = \{p_1, p_2, \ldots, p_N\}$ (with $N \geqslant H_1$ and $N \geqslant H_2$) from the sets of regions S_1 and S_2. Such a process is needed to integrate the segmentation maps S_1 and S_2 so that the final parcels may correspond to homogeneous regions shared by X_1 and X_2. This is achieved by using an algorithm that implements the following two conditions:

$$(m, n) \in p_i \ \ if \ \ x_1(m, n) \in s_1^d \ \ \textbf{AND} \ \ x_2(m, n) \in s_2^l \tag{7}$$

where d and l are fixed for each p_j

$$\text{Pixels in } p_j \ \ (j = 1, 2, \ldots, N) \text{ are } connected \tag{8}$$

Expressions (7) and (8) guarantee that the parcels satisfy the conditions outlined in §2.

3.2. *Generation of the parcel-based difference image and thresholding*

At each time t_i, the parcel p_j is characterized by an R-dimensional feature vector, $F_i^j = (f_{i_1}^j, \ldots, f_{i_v}^j, \ldots, f_{i_R}^j)$, where $f_{i_v}^j$ is the v-th feature computed on all the grey-level values $x_i(m, n)$, $(m, n) \in p_j$. The number R and type of features to be used depend on the application and images considered. However, as changes in land-covers can generally be associated with variations in both the grey-level values and the textural characteristics of the pixels in a parcel, we suggest using a set of features that consider these two aspects. As an example, the following two features can be computed:

$$\text{Mean}_i^j = \frac{1}{M_j} \sum_{(m,n) \in p_j} x_i(m, n) \tag{9}$$

$$\text{Entropy}_i^j = \sum_{g=0}^{255} \pi_i^j(g) \log_2 \pi_i^j(g) \tag{10}$$

where $\pi_i^j(g)$ is the probability that the grey level g occurs at time t_i in the parcel p_j. It is worth noting that the features can be computed in more than a single spectral band. This increases the size of the feature vector, but it may result in a more reliable characterization of the parcels.

At this point, the difference image X_d is computed at the parcel level. The values of the pixels that make up the parcel p_j in the difference image are given by:

$$x_d(m, n) = |F_2^j - F_1^j|,\ (m, n) \in p_j \tag{11}$$

Finally, the change-detection map can be produced by thresholding the difference image according to a classical strategy (Singh 1989, Bruzzone and Serpico 1997b).

A simple strategy associates the generic pixel *(m,n)* with a changed area if the following condition is satisfied:

$$x_d(m,n) > \overline{x_d} + t \cdot \sigma_d \tag{12}$$

where $\overline{x_d}$ and σ_d are the mean value and the standard deviation of the distribution of pixel values in the difference image, respectively, and t is a threshold parameter derived from experiments.

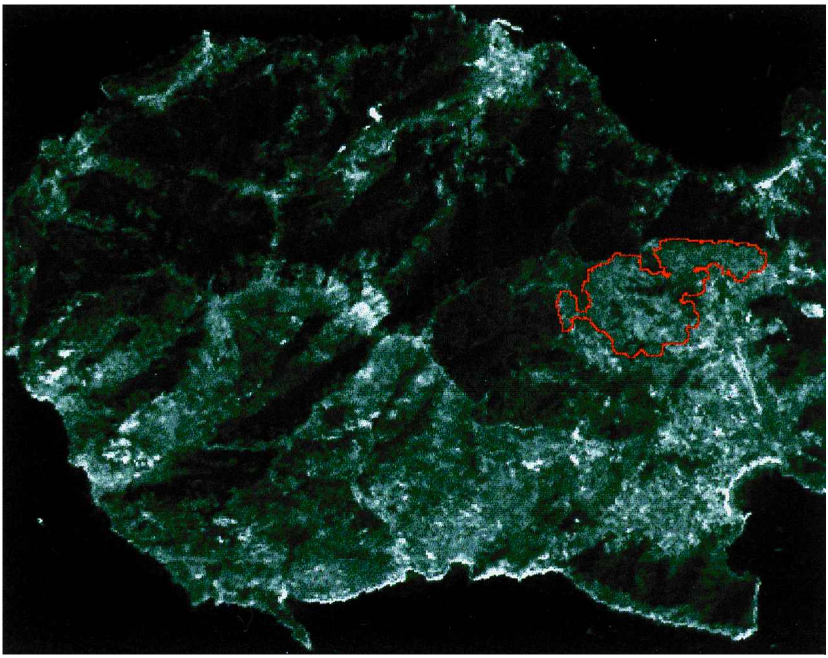


Figure 1. A Landsat TM band 2 sub-image (414 × 326 pixels) of the Island of Elba acquired in August 1992. The area damaged by a wildfire (255.78 ha) is outlined.

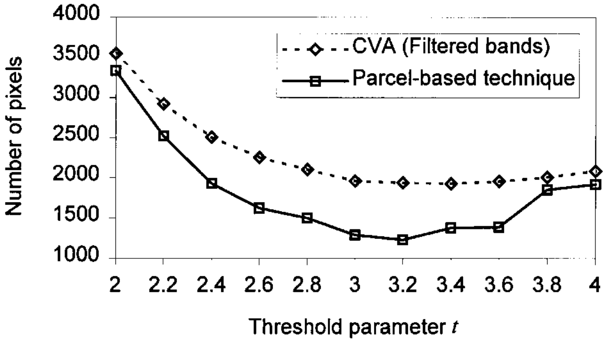
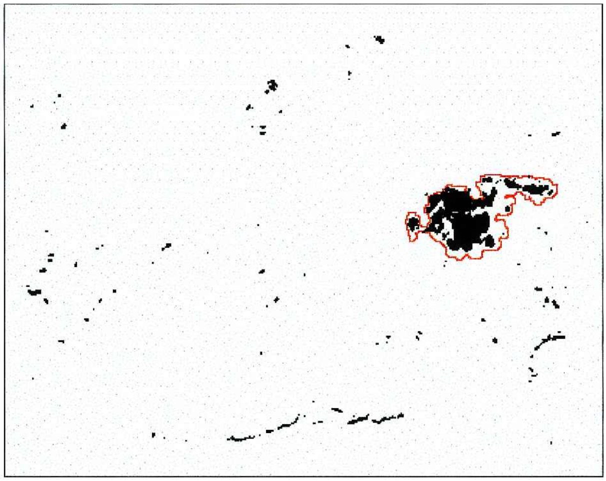
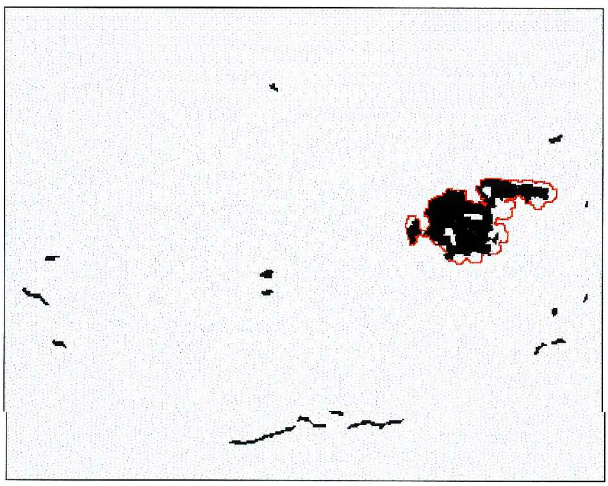


Figure 2. A comparison of the behaviours of the overall change-detection errors versus the values of the threshold parameter t for the proposed and CVA techniques.



(*a*)



(*b*)

Figure 3. (*a*) Map of the changes identified with the CVA technique applied to the filtered images. The map corresponds to the minimum overall error made by this technique ($t=3.3$). (*b*) Map of changes identified by the proposed technique. The map corresponds to the minimum overall error made by this technique ($t=3.2$).

4. Experimental results

The dataset used in the experiments was composed of two co-registered Landsat-5 Thematic Mapper (TM) images acquired in the western part of the Island of Elba (Italy) in August 1992 and August 1994. A wildfire, which occurred in 1993, destroyed a significant part of the vegetation in the selected area. The damage is still evident in the August 1994 image (figure 1).

The results obtained by applying the proposed technique to the original images were compared with those yielded by the application of the classical Change Vector Analysis (CVA) method to images that had been filtered using a 3×3 mean filter. We applied both the proposed and CVA techniques to spectral bands 1, 2, 3, 5 and 7 of the multispectral images, as preliminary experiments had demonstrated that this set of channels contained useful information for the detection of the damaged area. A region-growing algorithm (Nagao and Matsuyama 1980) was used to segment the 1992 and 1994 images for the proposed technique.

Figure 2 shows the behaviours of the overall change-detection errors versus the value of the decision threshold for the proposed and CVA techniques. As one can see, for all the threshold values considered, the presented technique resulted in the smallest errors. In particular, the minimum error generated by the proposed technique, i.e. 1281 pixels for $t = 3.2$ (see equation (12)), was much smaller than the one incurred by the CVA technique, i.e. 1936 pixels for $t = 3.3$. In greater detail, the proposed technique reduced the number of missed alarms, i.e. changed pixels identified as unchanged ones, from 1342 to 731, and the number of false alarms, i.e. unchanged pixels identified as changed ones, from 594 to 550.

Figures 3(*a*) and (*b*) show the maps of changes produced by the CVA and proposed techniques, respectively. A comparison of the maps indicates that the proposed technique allows a much more accurate location of the burnt area and a reduction in noise compared with the CVA technique applied to the filtered images. In addition, thanks to the adaptive definition of parcels, the presented technique exhibited higher precision in the detection of the border of the damaged area.

5. Conclusions

In this letter, a novel adaptive parcel-based technique for unsupervised change detection has been presented. Experimental results have shown the effectiveness of the proposed technique, which sharply reduced the overall change-detection error, as compared with the CVA technique applied to images filtered by using a mean filter. In particular, the adaptive nature of parcels allowed a notable reduction in noise and an accurate location of the border of the changed area.

The proposed technique can perform change detection by using different kinds of measures to characterize the properties of each parcel. This peculiarity is important in the cases where changes involve variations in the spatial–contextual properties of an image rather than in the grey-level values of single pixels.

Acknowledgements

The authors wish to thank the anonymous referees for their constructive criticisms. This work was supported by the Italian Space Agency (ASI).

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