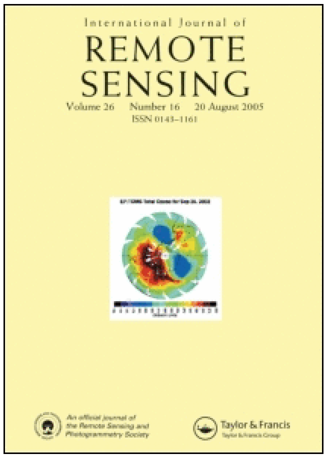

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A minimum-cost thresholding technique for unsupervised change detection

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Abstract. We propose an automatic thresholding technique for difference images in unsupervised change detection. Such a technique takes into account the different costs that may be associated with commission and omission errors in the selection of the decision threshold. This allows the generation of maps in which the overall change-detection cost is minimized, i.e. the more critical kind of error is reduced according to end-user requirements.

1. Introduction

Change-detection maps are a useful support for decision making (risk assessment, natural disaster monitoring, damage evaluation). Most unsupervised change-detection techniques proposed in the remote-sensing literature aim at minimizing the overall change-detection error, without taking into account the practical objective for which maps are produced (Singh 1989, Bruzzone and Serpico 1997). However, in many applications, commission errors (which occur when unchanged pixels are detected as changed ones) and omission errors (which occur when changed pixels are identified as unchanged ones) involve different consequences in terms of decision making. In these cases, the minimization of the overall error is not the most suitable goal for the change-detection process. For example, let us assume that the objective of change detection is the identification of damages caused by a natural disaster (e.g. wildfire, flood). In this context, the end-user (e.g. civil protection) may prefer a change-detection map where all the possible damaged areas are pointed out (even if some of them are wrong), rather than a map where some damaged areas are missing. This means that omission errors are more costly than commission ones. Consequently, the goal of change detection should be the generation of a map in which omission errors are minimized. This objective can be attained by associating different weights (i.e. costs) with omission and commission errors, and then performing a change-detection process that minimizes the overall cost involved by errors. The value of each cost depends on the application considered, and should be defined on the basis of the end-user's experience.

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In a recent work, the authors presented a fully automatic approach to unsupervised change detection based on the Bayes rule for minimum error (BRME). Such an approach aims to minimize the overall change-detection error (Bruzzone and Fernández Prieto 2000). In this Letter, we present an extension of the aforementioned work that attempts to provide a more application-oriented tool for monitoring land-cover changes. The main novelty of the proposed technique lies in the definition of the unsupervised change-detection problem in terms of the Bayes rule for minimum cost (BRMC) (Fukunaga 1990). This allows the generation of change-detection maps in which the more critical type of error is minimized according to end-user requirements.

2. The proposed method

Let us consider two co-registered multispectral images, $\mathbf{X}_1$ and $\mathbf{X}_2$, acquired in the same area at two different times, t_1 and t_2. Let X be a random variable that represents the values of the pixels in the difference image $\mathbf{X}_D$ obtained from $\mathbf{X}_1$ and $\mathbf{X}_2$ by applying the classical change vector analysis (CVA) technique (Singh 1989). For a given pixel in $\mathbf{X}_D$, we want to select one of two opposite classes ω_c (i.e. changed pixels) and ω_u (i.e. unchanged pixels), by considering the different costs associated with commission and omission errors. We formulate this problem in terms of the Bayes rule for minimum cost (BRMC). Accordingly, changes can be detected by using the following decision strategy (Fukunaga 1990):

$$R(\omega_c/X_D^{ij}) \underset{X_D^{ij} \in \omega_c}{\overset{X_D^{ij} \in \omega_u}{\lessgtr}} R(\omega_u/X_D^{ij}) \tag{1}$$

where X_D^{ij} is the grey-level value of the pixel (i, j) in the difference image and $R(\omega_p/X_D^{ij})$, $p=\{u, c\}$, is the conditional cost of deciding on $X_D^{ij} \in \omega_p$, given the pixel X_D^{ij}. Each conditional cost is defined as:

$$R(\omega_p/X_D^{ij}) = c_{pu} P(\omega_u/X_D^{ij}) + c_{pc} P(\omega_c/X_D^{ij}), \qquad p=\{u, c\} \tag{2}$$

where c_{pq}, $q=\{u, c\}$, is an integer value that defines the cost of classifying a pixel belonging to the class ω_q as a pixel belonging to the class ω_p, and $P(\omega_p/X_D^{ij})$ is the posterior probability of the class ω_p, given the pixel X_D^{ij}. The values of c_{pq} should be set by the end-user in accordance with the specific application considered (see Bruzzone (2000) for a more detailed discussion on the use of costs in the analysis of remote-sensing images.)

Taking into account both the definition of conditional cost and the fact that typically $c_{pq}=0$, $\forall p=q$, equation (2) can be rewritten as (Fukunaga 1990):

$$\frac{c_{uc} P(\omega_c)}{c_{cu} P(\omega_u)} \underset{X_D^{ij} \in \omega_u}{\overset{X_D^{ij} \in \omega_c}{\lessgtr}} \frac{p(X/\omega_u)}{p(X/\omega_c)} \tag{3}$$

where $p(X/\omega_u)$, $p(X/\omega_c)$ and $P(\omega_u)$, $P(\omega_c)$ are the conditional density functions and the *a priori* probabilities of the classes ω_u and ω_c, respectively. As we deal with an unsupervised problem, the above-mentioned terms cannot be estimated by using a training set. To compute these statistical parameters in an unsupervised way, we propose to use the method presented by the authors in Bruzzone and Fernández Prieto (2000). Then, on the basis of the resulting estimates, the decision threshold

$\hat{T}_0$ can be derived by solving the following equation in terms of the variable X:

$$\frac{c_{nu}P(\omega_c)}{c_{cu}P(\omega_u)} = \frac{p(X/\omega_u)}{p(X/\omega_c)} \tag{4}$$

From an operational point of view, we can obtain a more useful expression by rewriting (4) as

$$\frac{P(\omega_c)}{kP(\omega_u)} = \frac{p(X/\omega_u)}{p(X/\omega_c)} \tag{5}$$

where $k = c_{uc}/c_{cu}$. The parameter k makes it simpler to use the BRMC as it establishes the proportion between the costs instead of assigning a numerical value to each cost (this may turn out to be a difficult task in some applications).

Once the threshold $\hat{T}_0$ has been selected, the map of changes can be easily achieved by applying the following rule:

$$\begin{aligned} &\text{If } X_D^{ij} \geqslant \hat{T}_0 \\ &\text{then } X_D^{ij} \in \omega_c \\ &\text{else } X_D^{ij} \in \omega_u \end{aligned} \tag{6}$$

It is worth noting that, when $c_{uu} = c_{cc} = 0$ and $c_{cu} = c_{uc}$ (i.e. $k = 1$), minimizing the overall change-detection cost coincides with minimizing the overall change-detection error (Fukunaga 1990).

3. Experimental results

The data set used in the experiments consisted of two co-registered images (414 pixels × 326 pixels) acquired in the western part of the Island of Elba, Italy, by the Thematic Mapper (TM) on the Landsat-5 satellite in August 1994 and September 1994, respectively. As an example, figure 1 shows channel 4 (i.e. a near-infrared spectral channel) of the September image. As one can see, a wildfire destroyed a significant portion of the vegetation between the above two dates. The difference image was computed by applying the CVA technique to spectral bands 4 and 7 of the considered multi-spectral images (such spectral bands were found to be very effective in detecting burnt areas).

To assess the effectiveness of the proposed technique, different experiments were carried out assuming two opposite cases that may occur in real applications: (1) the end-user considers the underestimation of a burnt area (i.e. omission error) as the more critical error; (2) the end-user requests a final change-detection map where areas erroneously identified as burnt ones (i.e. commission errors) are minimized. The results obtained in both cases were evaluated using the minimum-error case (i.e. $k = 1$) as the reference one.

In the first case, the cost c_{uc} associated with omission errors was assumed to be k times as large as the cost c_{cu} associated with commission errors. Different trials were carried out with the k value ranging from 2 to 10 to simulate different end-user requirements. As one can see in table 1 by increasing the k values, the number of omission errors (i.e. the more critical errors) was sharply reduced from 282 pixels (for $k = 1$) to only 59 pixels (for $k = 10$). On the other hand, an increase in the number of commission errors (i.e. the less costly errors) was observed (from 142 pixels to 846 pixels). This is a reasonable behaviour that, according to the strategy adopted

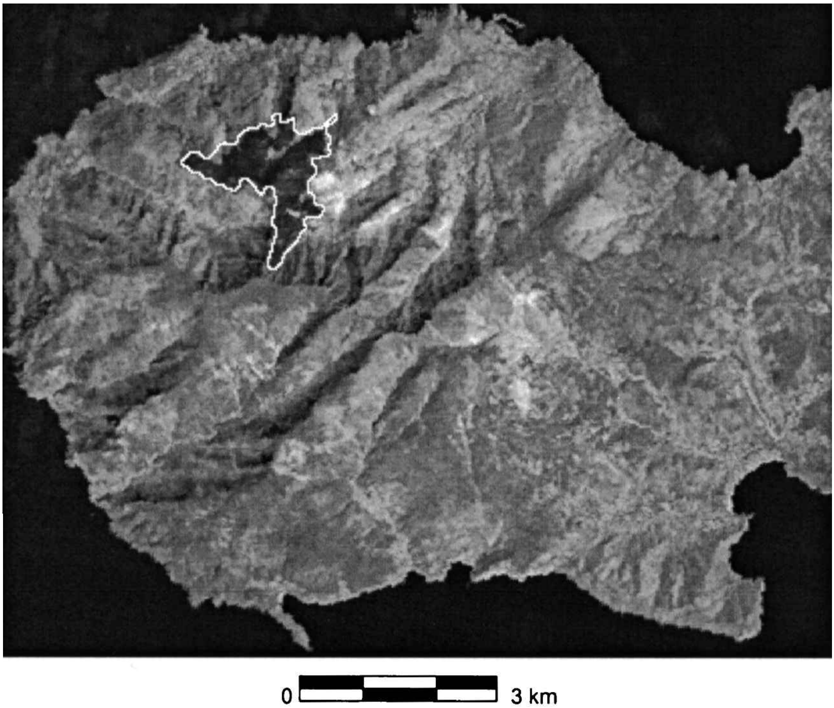


Figure 1. A TM band-4 sub-image (414 pixels × 326 pixels) of the Island of Elba acquired in September 1994. The area damaged by a wildfire (217.26 ha) is indicated by the white polygon.

Table 1. Commission and omission errors incurred by the proposed technique for k values ranging from 2 to 10 (i.e. the omission errors are regarded as the more costly errors). For the sake of comparison, the results obtained for $k=1$ are also shown.

$k=c_{nc}/c_{cn}$	Threshold obtained	Commission errors	Omission errors
1	85	142	282
2	82	233	211
5	78	367	151
10	74	846	59

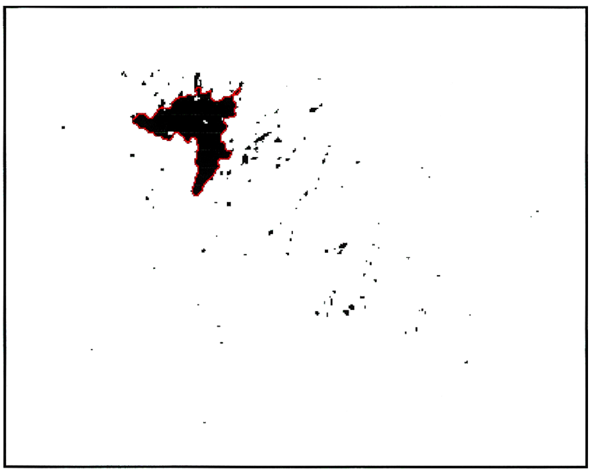
by the end-user to define the error costs, leads to the minimization of the final overall cost of change-detection errors.

In the second case, the cost c_{uc} associated with omission errors was assumed to be k times as small as the cost c_{cu} associated with commission errors. Table 2 shows the results obtained for different values of k (in a range from $k=0.5$ to $k=0.1$). As a consequence of the cost-selection strategy adopted in this case, the number of commission errors (i.e. the more critical errors) was sharply reduced from 142 pixels (for $k=1$) to only 32 pixels (for $k=0.1$), whereas the number of omission errors (regarded, in this case, as the less critical errors) increased from 282 pixels to 526 pixels. This result meets the end-user's requirements, in agreement with the specific costs chosen in this second case.

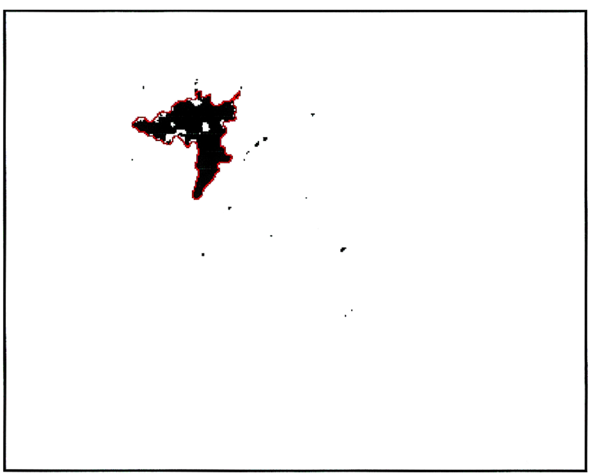
Figures 2(a) and 2(b) show the maps of changes obtained by the proposed

Table 2. Commission and omission errors incurred by the proposed technique for k values ranging from 0.5 to 0.1 (i.e. the commission errors are regarded as the more costly errors). For the sake of comparison, the results obtained for $k=1$ are also shown.

$k=c_{nc}/c_{cn}$	Threshold obtained	Commission errors	Omission errors
1	85	142	282
0.5	88	85	340
0.2	92	54	443
0.1	95	32	526



(a)



(b)

Figure 2. Change-detection maps obtained by the application of the proposed technique: (a) $k=5$; (b) $k=0.2$. The changed area is indicated by the red polygon.

approach for $k = 5$ and $k = 0.2$, respectively. As one can see, in figure 2(*a*), the number of omission errors is significantly smaller (almost all the burn area was identified as changed) than the number of less critical commission errors (in this case, omission errors were considered five times more critical than commission errors). On the contrary, in figure 2(*b*), commission errors were almost completely eliminated, whereas some omission errors (considered less critical in this case) are still evident in the image. Both results confirm the effectiveness of the proposed automatic technique.

4. Conclusions

We have proposed an automatic technique to select the decision threshold for the difference image in unsupervised change-detection problems. This technique provides end-users with a powerful tool for taking into account the different costs that may be associated with commission and omission errors in the change-detection process. Consequently, it represents a useful support for decision-making operations, as it allows end-users to obtain reliable change-detection maps in which the more critical kind of error is minimized.

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