AN A-CONTRARIO APPROACH FOR UNSUPERVISED CHANGE DETECTION IN RADAR IMAGES

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1. INTRODUCTION

The detection of changes occuring on the Earth surface after a disaster concern applications which are often related to a context of emergency, requiring a rapid mapping with few a priori knowledge on the type of changes. Such aim highly motivates the development of generic change detection tools for the analysis of heterogeneous time series (optical and radar images) as, for many applications, the first acquisition which is available after the event of interest needs to be utilized, whatever the weather or the lightning conditions. Radar images are then more likely to be used and their use plays a key role for change detection even though the presence of speckle noise makes particularly difficult the generation of robust change indicators. Recently, [1] introduced a new change indicator based on the Kullback-Leibler Divergence (KLD). This latter outperforms standard detectors dedicated to radar images (e.g. mean ratio detector), involving the four first order statistics computed over a window of a given size (when classical detectors are restricted to the use of first order statistics). Indeed, previous work [2] proved the interest of second and third order statistics for progressive changes in time series. Moreover, an important asset of this indicator is that it depends on an analyzing window-size (over which computing the statistics) which can be related to the scale of changes. Here, the approach we propose uses as a unique input a multiscale series of KLD change indicator images (*i.e.* computed for various window-sizes) in order to generate a change map between two dates and to provide the scale at which changes are the most meaningful. Observing such multiscale series, areas of changes can be characterized as areas where the KLD values vary a lot when the window-size varies. Conversely, areas where the KLD values remain stable when the window-size varies are considered as unchanged. Let W be the number of window-sizes that are considered (*i.e.* the number of images in the multiscale series) and $(x_1(i), \cdots, x_W(i))$ be the vector of KLD value obtained for a pixel i for window-sizes 1 to W. As the kind of changes to detect can have various sizes and intensities which are *a priori* unknown in most applications, we focus on the problem of the unsupervised choice of a threshold enabling a robust detection without any *a priori* information.

2. AN APPROACH FREE OF PARAMETER

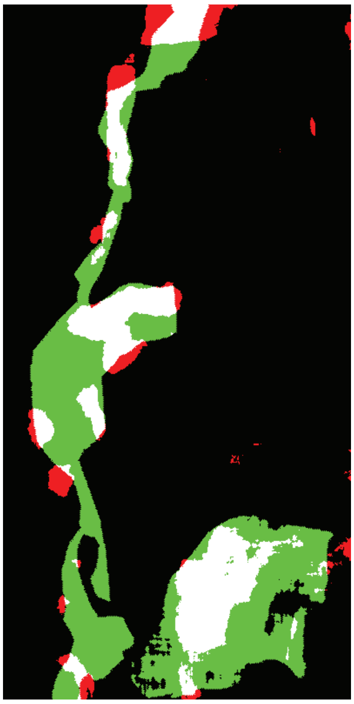
Following the a-contrario principle [3], we introduce a measure of meaningfulness based on the amount of surprise of observing a given KLD value in a naive random context. In a probabilistic framework, for all window-size w, the observed value x_w is a realization of the random variable X_w. As a naive random context, we assume that the random variables X_w are independent and follow a Gaussian law with mean 0 and variance 1 (each image of the input series being normalized). Hence, the probability of observing x_w by chance is $\mathbb{P}(X_w(i) \geq x_w(i))$. An upper bound for the expected number of false alarms can then be obtained simply by multiplying this probability by the number of tests we perform on the image (*i.e.* W). Then, the amount of surprise is measured by a *number of false alarms* defined by

$$F(i, w) = W \times \mathbb{P}(X_w(i) \geq x_w(i)), \tag{1}$$

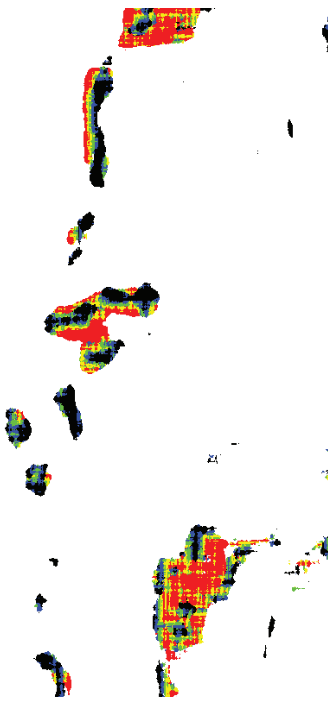
and the value observed for a pixel i and a window-size w is said to be $\varepsilon-$ meaningful if it satisfies $F(i, w) \leq \varepsilon$ (ε being a positive real number). Such definition ensures an expected number of ε-meaningful values less than ε in the naive random context. This property is fundamental as it means that ε controls the expected number of false alarms. We simply set ε to 1 thus making the approach parameterless meanwhile ensuring less than 1 false alarm on the average. A pixel i of the image domain is then detected as “changed” if there exists a window-size w such that $F(i, w) \leq 1$. In addition, the window-size which minimizes $F(i, w)$ is considered as the scale of the detected change.

3. APPLICATION TO REAL DATA

Here, we present a real case of application for change detection using a couple of Radarsat images of Goma (D. R. of Congo) acquired before and after the eruption of the Nyiragongo volcano (in January 2002). Computing the KLD (see [1]) between these two images for window-sizes ranging from 5 to 51, a multiscale series of KLD change indicators is generated. Using this series as an input and without any additional parameter, our approach allows to detect meaningful changes and their scale of appearance (*i.e.* the window-size for which the KLD measure is the most significant). The result obtained is compared to a change map produced using ground measures. Figure 1 (a) shows the change map where pixels that have been correctly detected as unchanged are represented in black, those correctly detected as changed are in white, missed detections are in green, and false alarms are in red. Figure 1 (b) shows the scale at which changes have been detected: the smallest window-size values are represented in black and the largest in red. The performance of the method for controling the number of false alarms is confirmed as only 2.4% of false alarms have been observed but there is a large amount of missed detection eventhough the overall error percentage is $15,7\%$. Beyond the fact that it is fully unsupervised and free of *a priori*, an interesting aspect of this approach is that it provides the scale of detection. However, an extension of this approach in a vectorial context is being considered in order to use the multiscale profile for decision.



(a) Change map.



(b) Scale of detected changes.

Fig. 1. Change detection results obtained using our approach. On the left: unchanged pixels detected as such are represented in black, pixels that are correctly detected as change are in white, missed detections in green and false alarms in red. On the right: scale of the detection. Pixels that have been detected using a window $w \in [25, 31[$ are represented in black, $w \in [31, 37[$ in blue, $w \in [37, 43[$ in green, $w \in [43, 49[$ in yellow and $w \in [49, 51]$ in red.

4. REFERENCES

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