GENERAL FRAMEWORK ON CHANGE DETECTION IN A SPARSE DOMAIN

Abdourrahmane M. Atto, Grégoire Mercier and Dominique Pastor

Institut TELECOM; TELECOM Bretagne
CNRS UMR 3192 Lab-STICC, team CID
Technopôle Brest-Iroise,
CS 83818, F-29238 Brest Cedex 3, France

1. INTRODUCTION

This paper makes the link between theoretical framework of change detection techniques that may be found in the literature and change detection strategy that can be implemented with remote sensing data.

At present time, the presentation focuses on two-date change detection from mid-resolution radar images. Further investigations are made to extend the detection to multi-date series. In fact, the number of observation (*i.e.* images) is linked to the dimension of the problem.

From the literature, one can state that the problem of detecting changes may be drawn from the detection of a *change*-signal blurred in the noise. Then, the noise stands for a stable observation, useless for detecting changes. This point of view may be written as:

$$\boldsymbol{y} = \begin{cases} \boldsymbol{x} + \boldsymbol{\varepsilon} & \text{on presence of } \textit{change}\text{-signal} \\ \boldsymbol{\varepsilon} & \text{when no } \textit{change}\text{-signal is to be detected.} \end{cases} \tag{1}$$

$\boldsymbol{y}$ is the observation (issued from the sampling of the random value [RV] $\boldsymbol{Y}$) and $\boldsymbol{x}$ stands for the *change*-signal to be detected.

The link between the detection of the signal $\boldsymbol{x}$ from a noisy observation $\boldsymbol{y}$ and the change detection from a pair of SAR images is achieved by considering multidimensional observation. $\boldsymbol{Y}$ may be considered to as a RV that is sampled in $\mathbb{R}^2$ for bi-date change detection purpose:

$$\boldsymbol{Y} = \begin{pmatrix} \text{img}_1 \\ \text{img}_2 \end{pmatrix}.$$

Hence, the problem of detecting $\boldsymbol{x}$ can be resolved by following [1]. In that case, noise $\boldsymbol{\varepsilon}$ has to be considered to follow a Gaussian law. No hypothesis is made on $\boldsymbol{x}$ except that it has to be less present than absent (*i.e.* for change detection purpose, change has to be limited in area in comparison to the size of the scene). Initial formulation shows that the decision on the presence of $\boldsymbol{x}$ depends on the variance of ε. Here (in 2-dimension formulation), the decision is based on the covariance matrix.

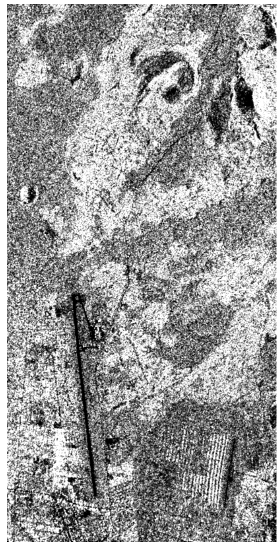
Then the main problem is to consider that normal observation follows Gaussian law. This can be resolved by considering the wavelet packet transform. In [2, 3], it has been proved that a sequence of wavelet packet coefficient converge in distribution to white Gaussian processes when the resolution level increases. Then, the sparsity concept, closely linked to the wavelet transform, may be used to perform estimation threshold for detecting signal in a Gaussian noise [4]. In order to increase the sparsity of the signal, a preprocessing filtering scheme is proposed based on a encapsulated median filtering called *turbo median*.

The following figures show change detection example from the pair of Radarsat images acquired before and after a lava flow over the city of Goma (R.D. Congo). The scatter-plots show the difference in shape of the distribution of the $\boldsymbol{y}$ samples, through the sparse representation, between a change and a no-change area. It makes the link to the Kullback-Leibler distance criteria which is used with success to detect changed from a pair of radar images [5]. In the present case, marginal pdfs are turned to be Gaussian (which helps the parameter estimation) while the decision criterion used the overall covariance matrix.

References

[1] D. Pastor, R. Gay, and A. Gronenboom, "A sharp upper bound for the probability of error of likelihood ratio test for detecting signals in white gaussian noise," *IEEE Transactions on Information Theory*, vol. 48, no. 1, pp. 228–238, Jan. 2002.

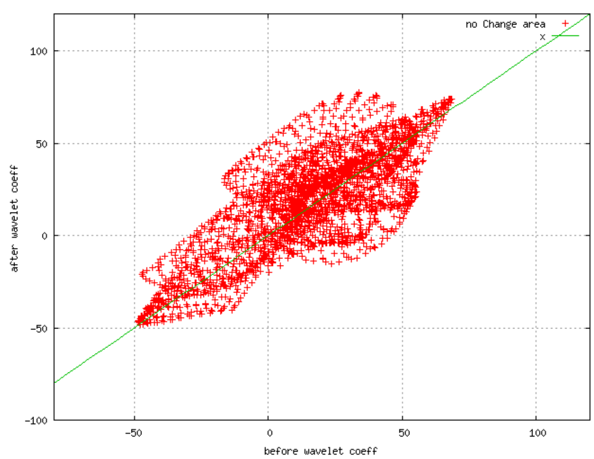
Before image

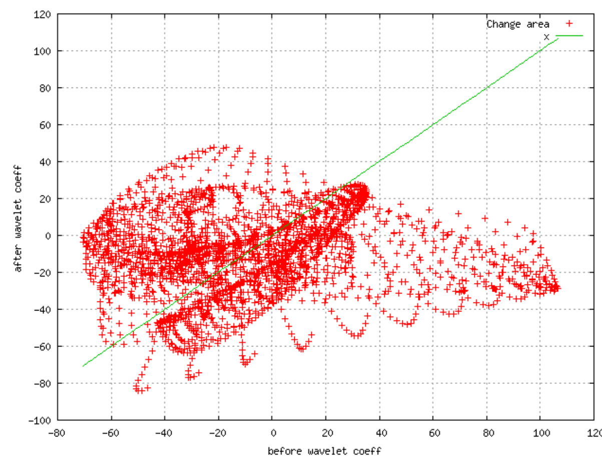


After image

Turbo Median 9×9

Initial image and typical example of the pre-processing step that increase sparsity of the observation





Typical example of a scatter-plot issued from a 50×50 sliding window on a no change area (left) and on a change area (right).

[2] A. M. Atto and D. Pastor, "Limit distributions for wavelet packet coefficients of band-limited stationary random processes," *European Signal Processing Conference, EUSIPCO,* Lausanne, Switzerland, August 25-28, 2008.

[3] A. M. Atto and D. Pastor, "Central limit theorems for wavelet packet decompositions of stationary random processes," Submitted to *IEEE Transactions on Signal Processing,* `http://aps.arxiv.org/abs/0802.0797v2`, 2008.

[4] A. M. Atto, D. Pastor, and G. Mercier, "Detection threshold for non-parametric estimation," *Signal, Image and Video Processing, Springer*, vol. 2, no. 3, Sept. 2008.

[5] J. Inglada and G. Mercier, "A new statistical similarity measure for change detection in multitemporal sar images and its extension to multiscale change analysis," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 5, pp. 1432–1445, 2007.