ROBUST LOW-RANK CHANGE DETECTION FOR SAR IMAGE TIME SERIES

A. Mian[*,†], *A.Breloy*[‡], *G. Ginolhac*[*,†] *and J.-P. Ovarlez*[*,¶]

[*] SONDRA, CentraleSupélec, Université Paris-Saclay, F-91190, Gif-sur- Yvette, France
[†] LISTIC, Université Savoie Mont-Blanc, F-74944, Annecy le Vieux, France
[‡] LEME, Université Paris-Nanterre, IUT Ville d'Avray, LEME-EA4416, France
[¶] DEMR, ONERA, Université Paris-Saclay, F-91123, Palaiseau, France

ABSTRACT

This paper considers the problem of detecting changes in multivariate Synthetic Aperture Radar image time series. Classical methodologies based on covariance matrix analysis are usually built upon the Gaussian assumption, as well as an unstructured signal model. Both of these hypotheses may be inaccurate for high-dimension/resolution images, where the noise can be heterogeneous (non-Gaussian) and where all channels are not always informative (low-rank structure). In this paper, we tackle these two issues by proposing a new detector assuming a robust low-rank model. Analysis of the proposed method on a UAVSAR dataset shows promising results.

***Index Terms*—** Change detection; Synthetic aperture Radar; Low Rank; Compound Gaussian;

1. INTRODUCTION

Analysis of Synthetic Aperture Radar (SAR) Image Time Series (ITS) has become a popular topic of study since it has many practical applications for Earth monitoring such as disaster assement or land-cover analysis. Developing reliable methodologies for Change Detection (CD) in SAR-ITS is thus an active topic of research. The CD problem is challenging due to the lack of ground truths, which does not allow to apply supervised methods from the image processing literature. Moreover, it is well known that SAR images are subjected to speckle noise, which makes traditional optical approaches unreliable. Under these conditions, unsupervised methodologies, often based on statistical tools, have been popular approaches in recent decades [1].

The CD problem can be seen as designing a distance. Among popular methodologies, Coherent Change Detection (CCD) [2] and the log-ratio operator [3] have received noticeable attention. However, these methodologies are limited to pairs of one-dimensional images, while modern sensors allow obtaining multidimensional ones (using e.g., polarimetric or spectro-angular channels [4, 5]). Exploiting this diversity allows an improvement of performance in terms of CD applications for SAR-ITS.

For multivariate data, the covariance matrix has been shown to be a relevant feature so as to assess changes [6]. Assuming a complex Gaussian model, [7] has considered statistical information theory to design a distance, while [8] have adapted covariance homogeneity tests from the statistical literature [9], such as the Generalized Likelihood Ratio Test (GLRT). These methodologies allow to reach good performance, but suffer nonetheless from two issues encountered in high-dimension/resolution images:

$i)$ The Gaussian model has been shown to be inaccurate in recent radar clutter analysis [10] due to the inherent heterogeneity of these images. In order to be robust to this non-Gaussianity, [11] proposed various GLRTs, assuming a Compound Gaussian distribution.

$ii)$ Standard detectors are derived assuming unstructured covariance matrices, while the signal of interest usually lies in a low-dimensional subspace (e.g., only one polarisation among HH, HV and VV).

In this scope, [12] proposed to extend some GLRT approaches to Low-Rank (LR) structured covariance matrices.

To enjoy the best of both worlds, this paper proposes a new detector based on both robust and LR model: we derive a GLRT for Compound Gaussian distributed observations that have a LR structured covariance matrix. This proposed detector is then applied for CD on a SAR-ITS UAVSAR dataset and exhibits promising results.

2. GENERIC FRAMEWORK

2.1. Data: We consider a multidimensional ITS, that means each pixel at a given date corresponds to a vector of data of dimension p. These p channels can correspond to a polarimetric diversity ($p = 3$), or to another kind of diversity such as a spectro-angular one, obtained through wavelet transforms [5]. The CD is applied using a local window arround the pixel of interest. Locally, the data set is denoted

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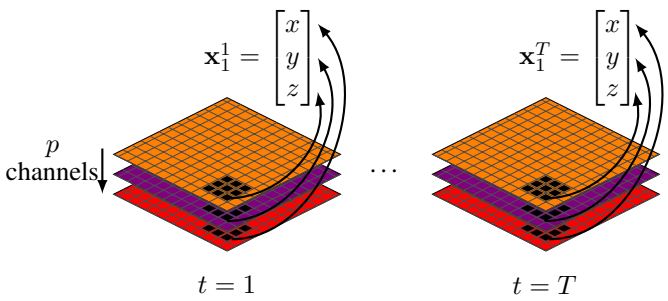

Fig. 1. Illustration of data for $p = 3$, $N = 9$. The pixels highlighted in black correspond to the local observations.

$\{\mathbf{x}_k^t\}_{(k,t)\in[\![1,K]\!]\times[\![1,T]\!]}$, corresponds to the concatenation of all channels for pixel at date t and spatial index k, as described in Figure 1.

2.2 GLRT for CD: For a given time t, the data is assumed to follow a given distribution of parameter $\boldsymbol{\theta}_t$, leading to the likelihood denoted $\mathcal{L}(\ \{\mathbf{x}_k^t\}_{k\in[\![1,K]\!]} \mid \boldsymbol{\theta}_t\ )$. The parameters $\boldsymbol{\theta}_t$ characterise the local data at each date. Hence, if there is a change, the parameter is expected to vary.

For the sake of clear exposition, we will focus on $T = 2$ (CD between two acquisitions), which can be straightforwardly extended to $T > 2$. The CD problem can be formulated as a binary hypothesis test:

$$\begin{cases} \mathrm{H}_0: & \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2 \quad \text{(no change)}, \\ \mathrm{H}_1: & \boldsymbol{\theta}_1 \neq \boldsymbol{\theta}_2 \quad \text{(change)}. \end{cases} \tag{1}$$

In order to derive a metric of decision, the Generalized Likelihood Ratio Test (GLRT), is considered. This test consists in computing the following quantity:

$$\hat{\Lambda} = \frac{\max\limits_{\boldsymbol{\theta}_1,\boldsymbol{\theta}_2} \prod_{t=1}^{2} \mathcal{L}\left(\ \{\mathbf{x}_k^t\}_{k\in[\![1,K]\!]} \mid \mathrm{H}_1;\ \{\boldsymbol{\theta}_1,\ \boldsymbol{\theta}_2\}\ \right)}{\max\limits_{\boldsymbol{\theta}_1} \prod_{t=1}^{2} \mathcal{L}\left(\ \{\mathbf{x}_k^t\}_{k\in[\![1,K]\!]} \mid \mathrm{H}_0;\ \boldsymbol{\theta}_1\ \right)}, \tag{2}$$

where $\{\boldsymbol{\theta}_1,\ \boldsymbol{\theta}_2\}$ (resp. $\boldsymbol{\theta}_1$) corresponds to the parameters of the distribution of the observations under H_1 (resp. H_0). Hence, to develop efficient detectors, the problem remains to select an assumed distribution (and corresponding parameters) that accurately reflects the behavior of the data. Additionally, depending on the assumptions, the evaluation of the GLRT may lead to complex optimization problems.

3. GLRTS ON COVARIANCE MATRICES

3.1. Gaussian CD [6]: Assuming Gaussian distributed samples, the CD can be performed by testing a change in the covariance matrix. The corresponding GLRT, denoted $\hat{\Lambda}_{\mathrm{G}}$ corresponds to (2) with the following distribution/parameters:

$$\mathbf{x}_k^t \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Sigma}^t) \quad \text{and} \quad \boldsymbol{\theta}_{\mathrm{G}}^t = \{\boldsymbol{\Sigma}^t\} \tag{3}$$

this test has a closed-form expression and is well studied in the statistical literature [8].

3.2. LR-Gaussian CD [12]: Radar signals usually lie in lower dimensional subspaces, leading to a LR structured covariance matrix. The Gaussian GLRT that accounts for this prior knowledge, denoted $\hat{\Lambda}_{\mathrm{LRG}}$, can be formulated as (2) with distribution/parameters:

$$\mathbf{x}_k^t \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Sigma}_R^t + \sigma^2\mathbf{I}) \quad \text{and} \quad \boldsymbol{\theta}_{\mathrm{LRG}}^t = \{\boldsymbol{\Sigma}_R^t\} \tag{4}$$

where $\boldsymbol{\Sigma}_R^t$ is the rank R signal covariance matrix and $\sigma^2\mathbf{I}$ is the covariance matrix of the thermal noise. More details about this GLRT (setting R, σ^2, computation...) can be found in [12] and section 5.2 of this paper.

3.3. Compound Gaussian CD [11]: For heterogeneous images, the Gaussian assumption may be a poor approximation of the underlying physics. In order to be robust to local power disparities, we can rely on the Compound Gaussian (CG) model (also referred to as a mixture of scaled Gaussian), which can accurately fit the empirical distribution of high-resolution data [10]. This model corresponds to a Gaussian one, where each realization is scaled by a local power factor τ referred to as texture (assumed unknown deterministic in this work). Hence, a corresponding GLRT for change detection, denoted $\hat{\Lambda}_{\mathrm{CG}}$, can be formulated as (2) with distribution/parameters:

$$\mathbf{x}_k^t \sim \mathcal{CN}(\mathbf{0}, \tau_k^t\boldsymbol{\Sigma}_t) \quad \text{and} \quad \boldsymbol{\theta}_{\mathrm{CG}}^t = \{\boldsymbol{\Sigma}^t, \{\tau_k^t\}_{k\in[\![1,K]\!]}\} \tag{5}$$

i.e., we test if both the covariance matrix $\boldsymbol{\Sigma}^t$ and the textures $\{\tau_k^t\}$ change between acquisitions. The computation of this quantity involves fixed-point equations that can be computed numerically. A study of this approach can be found in [11].

4. PROPOSED DETECTOR

In order to enjoy the improvement brought by both non-Gaussian and structure assumptions, we propose the following detector:

4.1. LR-Compound Gaussian CD: Assuming samples distributed as CG with a LR structured covariance matrix, the proposed GLRT, denoted $\hat{\Lambda}_{\mathrm{LRCG}}$, corresponds to (2) with distribution/parameters:

$$\begin{aligned} &\mathbf{x}_k^t \sim \mathcal{CN}(\mathbf{0}, \tau_k^t(\boldsymbol{\Sigma}_R^t + \sigma^2\mathbf{I})) \\ &\boldsymbol{\theta}_{\mathrm{LRCG}}^t = \{\boldsymbol{\Sigma}_R^t, \{\tau_k^t\}_{k\in[\![1,K]\!]}\} \end{aligned} \tag{6}$$

where $\boldsymbol{\Sigma}_R^t$ is the rank R signal covariance matrix and $\sigma^2\mathbf{I}$ is the covariance matrix of the thermal noise. Again, we test if both the covariance matrix and the textures change between acquisitions. The computation of this quantity involves optimisation techniques similar to ones used in [11] and [12]. The

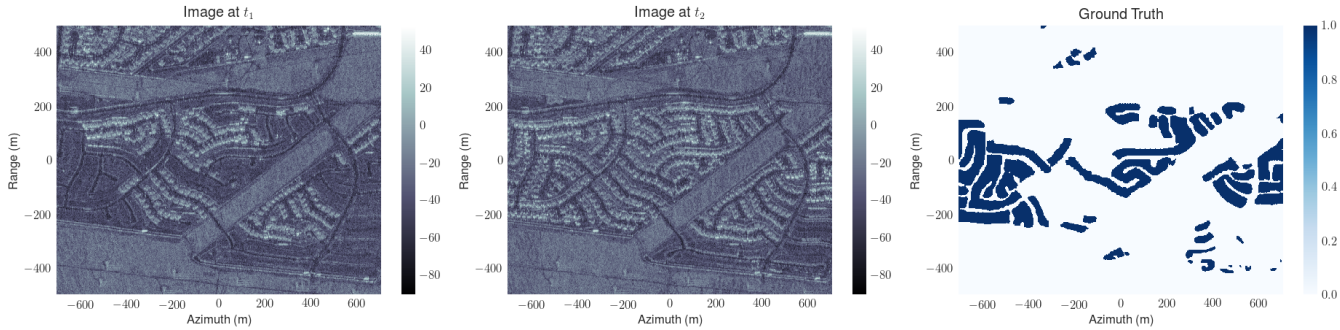

Fig. 2. UAVSAR Dataset used in this study. Left: April 23, 2009. Middle: May 15, 2011. Right: Ground Truth.

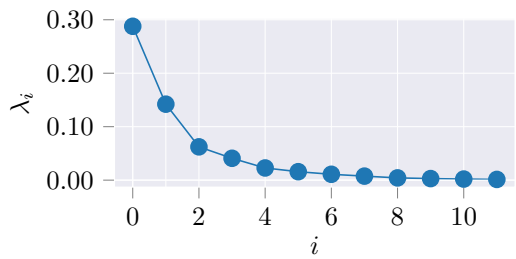

Fig. 3. Repartition of eigenvalues mean over the ITS.

cumbersome and technical calculus is left for a forthcoming paper[1]. The following section will present an application of this detector for CD in SAR-ITS.

5. STUDY ON REAL UAVSAR DATASET

5.1. Description of data

To assess the performance of the proposed method, a pair of two images from UAVSAR SanAnd_26524_03 Segment 4 dataset[2] has been chosen since a ground truth has been established in [7] by using comparison with optical data. The images presented in Figure 2, correspond to full-polarisation data with a resolution of 1.67m in range and 0.6m in azimuth. Since the scatterers present in this scene exhibit an interesting spectro-angular behaviour, each polarisation of these images has been subjected to the wavelet transform presented in [5], allowing to obtain images of dimension $p = 12$.

5.2. Selection of rank and noise level

To compute the proposed detector, the rank R must be estimated beforehand. Several approaches exist in the literature [13] for its estimation. In this paper, we consider a simple approach by considering the distribution of the mean of eigenvalues over the ITS plotted in Figure 3. For this dataset, $R = 3$ appears to be an interesting value to separate signal

[1]A python code for the proposed methodology is available at https://github.com/AmmarMian/Robust-Low-Rank-CD

[2]Available at https://uavsar.jpl.nasa.gov/.

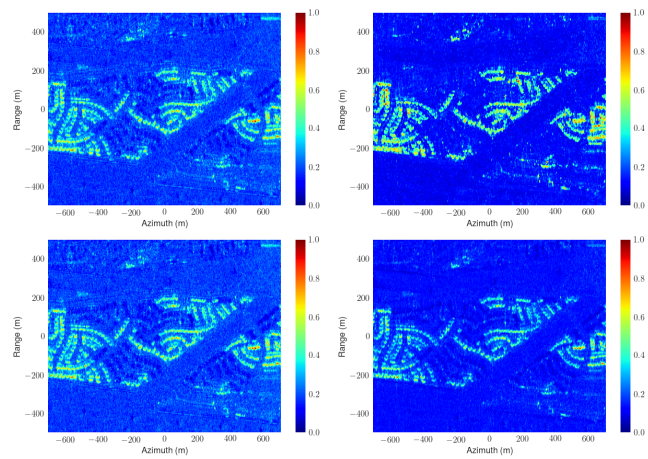

Fig. 4. Output of detectors (normalised) with $(p = 12, N = 25)$. Top-Left: $\hat{\Lambda}_{\mathrm{G}}$. Top-Right: $\hat{\Lambda}_{\mathrm{LRG}}$. Bottom Left: $\hat{\Lambda}_{\mathrm{CG}}$. Bottom Right: $\hat{\Lambda}_{\mathrm{LRCG}}$ (proposed).

from noise components. Notably, this rank gathers 81% of the total variance. The noise variance σ^2 is estimated locally with the mean of the $(p - R)$ lowest eigenvalues computed with an SVD of the SCM of all samples $\{\mathbf{x}_k^t\}$ in the patch.

5.3. Results

As a mean to assess the effectiveness of combining LR structure with a robust model, it is compared to the following detectors: i) the classic Gaussian statistic proposed in [6] (Section 3.1); ii) the LR Gaussian statistic of [12] (Section 3.2); iii) the CG statistic proposed in [11] (Section 3.3). Figure 4 presents the outputs of each detector for a window size of 5×5. It appears that the LR detectors outputs (right column) contain less visual false alarms compared to the non-LR ones, which is expected since the most relevant channels are used to compute the CD, making it less sensitive to noise.

Figure 5 shows the Receiver Operator Curve (ROC) for the results of Figure 4. The proposed method allows obtaining the best performance of detection for any given false

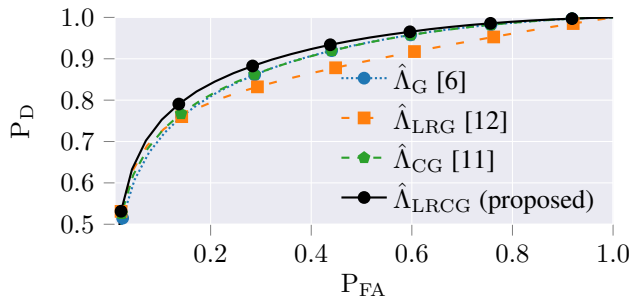

Fig. 5. Probability of detection P_D versus the the probability of false alarm P_{FA} with $(p = 12, N = 25)$

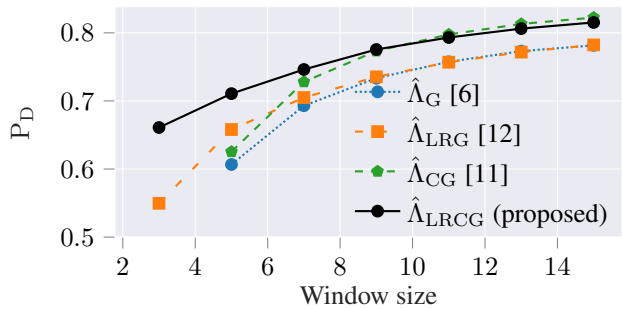

Fig. 6. P_D versus the size of window at $P_{FA} = 5\%$ with $(p = 12, R = 3)$

alarm rate, which is an interesting result. The gain is most apparent with regards to the LR Gaussian detector which performs poorly for false alarms rate greater than 10%. This is explained by the fact that an LR structure in Gaussian context results in the loss of some signal power while in our model, the texture parameters account for the entirety of this power.

Finally, Figure 6 shows the evolution of the performance in terms of P_D at $P_{FA} = 5\%$ when increasing the size of the window used to compute the detectors. Increasing the window improves the results at the cost of a resolution loss. The interest of LR methods is well demonstrated here: they allow to obtain good detection results with a lower size of window compared to their non-LR counterparts. The proposed method exhibits the best performance, which was to be expected given that it has been derived using a model more appropriated to the data.

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