Sequential Phase Linking : progressive integration of SAR images for operational phase estimation

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1 Abstract

In this paper, we address the topic of sequential integration of new Synthetic Aperture Radar (SAR) images in interferometric phase estimation. When a newly acquired data arrives, the data set expands and can be partitioned to two distinct blocks, one representing the historical SAR images and the other representing the newly acquired data. The proposed approach exploits sequential estimation of the covariance matrix of SAR images and the interferometric phases, taking the existing data set as prior information. This approach simplifies the continuous interferometric phase estimation by incorporating new data into the existing context. Furthermore, it presents the advantage of reduced computation time compared to the traditional approaches, making it a more efficient solution for operational displacement estimation.

2 Context

The short revisit cycle of the Sentinel-1 mission ($6-12$ days) enables the acquisition of unprecedented SAR data volumes. Once a new image arrives, most classical methods require the replay of the algorithm on the entire of or part of the data set. The literature has not extensively explored robust sequential processing of this data, as indicated by the limited number of studies addressing this specific topic. The most known sequential approach was developed in [1] where the main idea is to partition the entire stack of SAR images into m mini-stacks. The algorithm starts by treating the first mini-stack and then compressing it into a single virtual image through principal component analysis (PCA). The virtual image obtained is then connected to the next mini-stack, and so on. This approach, based on the standard PL [2–4] (which uses the modulus of the Sample Covariance Matrix (SCM) as a plug-in for the coherence matrix), requires an extended period to form the adequate fixed size mini-stack. This constraint limits the method's ability to respond to real-time needs.

3 Methodology

We propose an approach (namely S-MLE-PL) to tackle the difficulties arising from the growing volumes of SAR data produced by current and upcoming Sentinel-1 SAR mission. It enables the sequential integration of newly acquired data, yielding better results than classical approaches that process the entire data set at once. Additionally, the proposed sequential method offers the advantage of computational efficiency compared to the classic approaches.

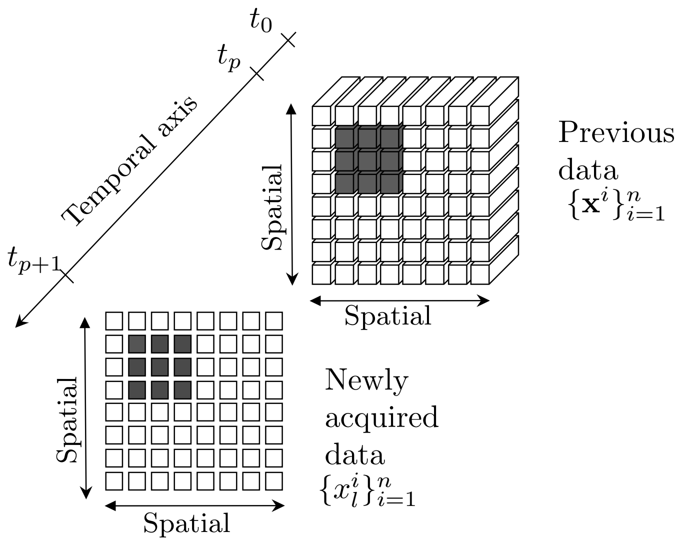


Figure 1: SAR data representation including both previous and recently obtained images. The local neighborhood of size n is denoted by gray pixels (sliding window).

We consider a stack of $l = p+1$ SAR images, for a given pixel, we define a local homogeneous spatial neighborhood of size n, denoted $\{\tilde{x}^i\}_{i=1}^n$, where $\tilde{\mathbf{x}}^i \in \mathbb{C}^l$, for all $i \in [\![1, n]\!]$. We can assume that each pixel of the local patch is distributed as a zero mean Complex Circular Gaussian (CCG) with a covariance matrix [5], i.e., $\tilde{\mathbf{x}} \sim \mathcal{N}(0, \widetilde{\mathbf{\Sigma}})$. Taking into account the phase closure property of the InSAR stack, the covariance matrix adheres to the following structure [6]:

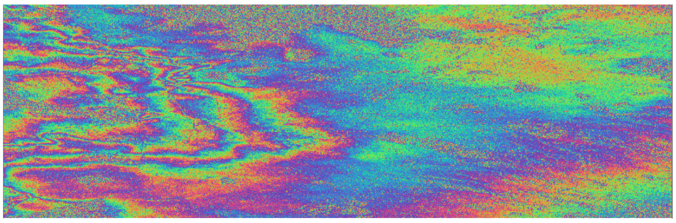
$$\widetilde{\mathbf{\Sigma}} = \tilde{\mathbf{\Psi}} \circ \tilde{\mathbf{w}}_{\boldsymbol{\theta}} \tilde{\mathbf{w}}_{\boldsymbol{\theta}}^H \tag{1}$$

where the symbol $\circ$ signifies element-wise (Hadamard) multiplication, $\tilde{\mathbf{\Psi}}$ is the real core of the covariance matrix. The hermitian structured covariance matrix can be rewritten as

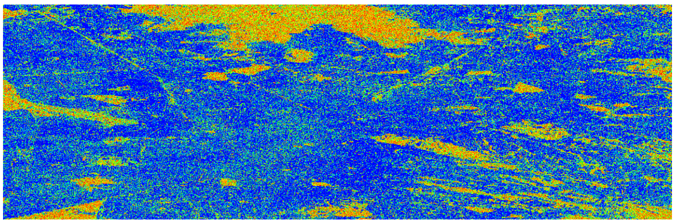
$$\widetilde{\mathbf{\Sigma}} = \begin{pmatrix} \mathbf{\Sigma} & w_{\theta_l}^* \mathrm{diag}(\mathbf{w}_\theta) \boldsymbol{\gamma}^T \\ \boldsymbol{\gamma} \mathrm{diag}(\mathbf{w}_\theta)^H w_{\theta_l} & \gamma_l \end{pmatrix} \tag{2}$$

where Σ denotes the covariance matrix between the previous SAR images, $\boldsymbol{\gamma}$ signifies the correlation vector between the newly acquired data and the previous ones, γ_l represents the variance value of the newly acquired data, $\mathbf{w}_\theta$ indicates the vector of phase difference exponential of the previous SAR images, and w_{θ_l} is the exponential of the phase of the latest data.

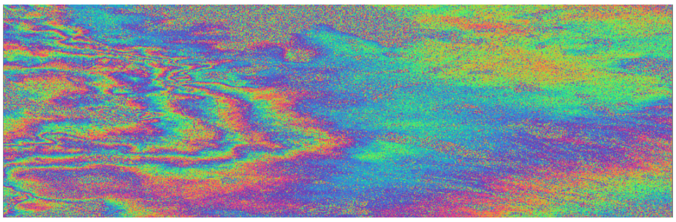
Considering the covariance matrix structure in (2) and assuming that $\{\tilde{x}^i\}_{i=1}^n$ follows a CCG distribution, the as-



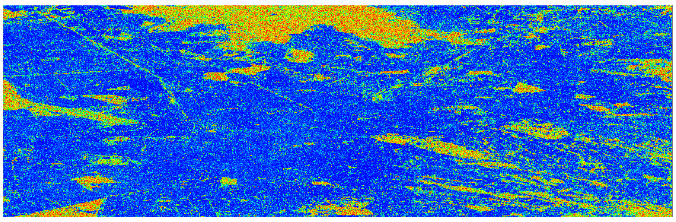
(a) Interferogram estimated by MLE-PL



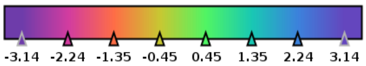
(b) A posteriori coherence estimated by MLE-PL



(c) Interferogram estimated by S-MLE-PL



(d) A posteriori coherence estimated by S-MLE-PL



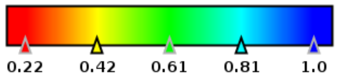


Figure 2: Comparisons of interferograms and a posteriori coherence for MLE-PL and S-MLE-PL.

sociated negative log-likelihood for the entire dataset can be expressed as:

$$\mathcal{L}_G(\boldsymbol{\gamma}, \gamma_l, w_{\theta_l}) \propto n \log(v) + \sum_{i=1}^{n} \frac{y^{i*} y^i}{v}. \tag{3}$$

where $y^i = x_l^i - w_{\theta_l} \boldsymbol{\gamma} \operatorname{diag}(\hat{\mathbf{w}}_\theta)^H \hat{\boldsymbol{\Sigma}}^{-1} \mathbf{x}^i$
and $v = \gamma_l - \boldsymbol{\gamma} \operatorname{diag}(\hat{\mathbf{w}}_\theta)^H \hat{\boldsymbol{\Sigma}}^{-1} \operatorname{diag}(\hat{\mathbf{w}}_\theta) \boldsymbol{\gamma}^T$

The PL problem [6] can be represented by a maximum likelihood approach for the covariance structure (1), assuming the Gaussian model for a given prior estimate of $\tilde{\boldsymbol{\Psi}}$. In this work, we propose to estimate simultaneously the coherence parameters and the new phase.

$$\begin{aligned} \min_{\boldsymbol{\gamma}, \gamma_l, \theta_l} \quad & \mathcal{L}_G(\boldsymbol{\gamma}, \gamma_l, w_{\theta_l}) \\ \text{subject to} \quad & \boldsymbol{\gamma}, \gamma_l \text{ real}, \ |w_{\theta_l}| = 1, \ \theta_1 = 0 \end{aligned} \tag{4}$$

For simplicity, we adopt the convention $\theta_1 = 0$, which is equivalent to $|[w]_1| = 1$. The optimization of $\mathcal{L}_G$, defined in (3), will be addressed in a unified manner using a Block Coordinate Descent (BCD) algorithm, where each parameter will have an analytical update form.

4 Real data

We use a stack of 20 SAR images over the Mexico City acquired every 12 days, from 14 August 2019 to 10 April 2020, corresponding to 8 months to assess the performance of the proposed S-MLE-PL approach. The interferograms estimated by both MLE-PL and S-MLE-PL approaches, are illustrated in Fig. (2a), (2c). In both cases, the multi-looking window, denoted as $n = 8 \times 8$, remains the same. The MLE-PL and S-MLE-PL methods yield the same results, however the sequential approach demonstrates significantly more reduced execution time than the MLE-PL when applied to real data. The quality of the PL may be assessed by the goodness of the fit between the observed phases and the estimated Fig. (2b) and (2d)

$$\gamma_{\text{post}} = \frac{\operatorname{Re}\left(\sum_{q=1}^{l} \sum_{i=q+1}^{l} \mathrm{e}^{(\Delta\theta_{iq} - (\hat{\theta}_i - \hat{\theta}_q))}\right)}{l(l-1)/2}$$

The closer the value of this parameter is to 1, the better the result. The sequential method shows values closer to 1 more often than the offline method, where a lot of noise and points colored in green and yellow can be seen, indicating values between 0.4 and 0.6.

5 Conclusions

We present a novel sequential PL approach that allows incorporating efficiently new SAR images in interferometric phase estimation in a PL framework. According to synthetic simulations and real data applications, the proposed S-MLE-PL approach presents the same performance and lower computational cost compared to MLE-PL.

6 Acknowledgement

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