Stable Target detection and coherence estimation in interferometric SAR stacks

Pietro Guccione
Dipartimento di Elettrotecnica ed Elettronica
Politecnico di Bari
Via Orabona, 4 - 70125 Bari, Italy
e-mail: guccione@poliba.it

Andrea Monti-Guarnieri, Stefano Tebaldini
Dipartimento di Elettronica e Informazione
Politecnico di Milano
Piazza Leonardo da Vinci 32, 20133 Milano, Italy
e-mail: monti@elet.polimi.it

Abstract—We propose a novel method to select long term coherent targets (Persistent Scatterers, PS) from a set of repeated pass interferometric acquisitions. The major assumption is that targets are so close together to share the same optical path. This leads to an efficient SVD-based estimator of the targets’ phase and then to PS detection. The estimated phase can be used to define the PS-coherence for each image. Being sensitive to acquisition and processing artifacts, the PS-coherence is a valuable tool for quality assessment of the interferometric stack. Results are shown with real datasets in both single and full polarization.

I. INTRODUCTION

The selection of stable targets or Persistent Scatterer is at the base of multi-temporal interferometric SAR processing, for applications like deformations estimations, for the retrieval of water vapor maps (the Atmospheric Phase Screen), and for calibration [1]. In [2] a non-coherent detection is proposed that exploits the statistics of amplitudes, the Dispersion Index, operating independently on each pixel along the whole stack. The non coherent approach is very efficient and robust, as phase independent, therefore it is commonly exploited for candidate selection in PS processors [3], however results are scanty when few images are available and it fails in the detection of medium quality targets from pure noise. Coherent approaches proved to be more sensitive in discriminating targets from noise and needing less images [4], [5]. Coherence estimation and detection can be performed in the time domain, on each target, by assuming that phase versus time is linear [2], [6], or basing on some model [7]. Eventually, one can avoid any assumptions on time domain behavior and exploit closely spaced targets [5], [8], [9], as in conventional coherence estimation [10]. However, in presence of temporal or baseline decorrelation, the selection of neighboring stable targets is a non-trivial task. One solution is to exploit interferograms with small temporal and spatial baselines and then combine the measures, like for the SBAS method [9], [3]. These methods works reasonably well, however complex and demands time and memory resources.

In this paper we propose a coherent approach that performs both the detection of stable targets and the estimation of the image phase by operating on very small patches of terrain (or imagettes) - say twenty pixels or so, but jointly in the whole stack. The method relies on the existence of targets coherent in time and space, say the PS, and assumes that two or more of them are located in an imagette, and shares the same “optical paths” [11], as Fig. 1 shows. The model is discussed in section II. Basing on this model, the detection of PS and the estimation of its phase is efficiently performed by iterating twice a Singular Value Decomposition (SVD). The method is discussed in section III and a performance analysis is there made, based on both numerical simulations and real datasets. Section IV proposes an “image coherence” index to assess the interferometric quality of the stack.

II. THE PS MODEL

Let us assume a stack of \( N_I \) interferometric images, i.e., acquired by repeated geometry and coregistered in the same master reference. The model for the \( p \)-th Persistent (or coherent) Scatterer in the \( n \)-th image, in the single polarization case, can be expressed as follows[2], [12]:

\[
y(n, p) = a(n) b(p) \exp(j\phi(n, p)) + a(n) w(n, p) \tag{1}
\]

where \( a(n) \) is the image amplitude, \( b(p) \) is the PS amplitude, \( \phi(n, p) \) is the phase of the \( p \)-th target in the \( n \)-th image and \( w(n, p) \) is zero mean Normal complex circular noise that accounts for thermal, clutter, model errors etc. The phase \( \phi \) accounts for a contribution proper of each target (that we will define as “intrinsic”), \( \psi_0 \), and as such non-dependent on temporal and geometric changes, and a further contribution that accounts for the overall target-to-sensor two way optical
The optical path accounts for the target height above the reference DEM, \( q(p) \), the target deformation (say subsidence etc) at the acquisition time, \( d(p) \), and the APS \( \alpha(n,p) \):

\[
\psi_r(n,p) = k_q(n)q(p) + k_d(n)d(p) + \alpha(n,p)
\]  

(3)

### III. PS DETECTION AND ESTIMATION

Detection of stable targets need as first step the estimation of the phase field, \( \phi(n,p) \), and its removal from data:

\[
y_d(n,p) = y(n,p) \exp(-j\hat{\phi}(n,p)) = a(n)b(p) \exp(j\phi_c(n,p)) + w'(n,p)
\]  

(4)

\( y_d \) being the phase compensated data, \( \phi_c \) the residual phase error and \( w' \) a normal distributed noise.

In absence of further assumption, the Maximum Likelihood phase estimator reduces to the trivial solution [12]:

\[
\hat{\phi}(n,p) = \mathbb{L}(y(n,p)).
\]

This estimate would be as noisy as the data, and when plugged into (4), would end in the non-coherent detection, that compares data amplitudes with the Dispersion Index [13]:

\[
D_I(p) = \frac{\frac{1}{N_I} \sum_{n=1}^{N_I} y_d(n,p)}{\sqrt{\frac{1}{N_I} \sum_{n=1}^{N_I} y_d^2(n,p) - \left( \frac{1}{N_I} \sum_{n=1}^{N_I} y_d(n,p) \right)^2}} = \frac{\hat{\mu}(p)}{\hat{\sigma}(p)}
\]  

(5)

However, if the phase is known, the ML detection of PS becomes both more accurate and robust, as shown in [3, 6]. The problem of providing a good estimate of the phase field has been approached by many different methods [2, 9, 8, 13]. These processors estimate the components of the phase field in (3) by taking advantage of their statistical properties: the APS being lowpass in space, the deformations lowpass in time, and the elevation linearly related to the baseline. These components are then reasssembled to provide the phase \( \hat{\phi} \) and then coherent detection follows after (4). Quite good results are achieved, yet with a time consuming and complicated procedure. Furthermore some attentions are needed to get convergence, as a suitable number of images (say tens) [13], [7], [5].

The approach proposed here follows the idea in [11], [14] to estimate the PS phase by exploring very small windows, say imagettes of \( N_{rg}3 \times N_{az}7 \) samples (this value has been find optimal in processing real datasets), but jointly on the whole stack. The window is so small that not only the APS, but also the topography and the deformations can be hold constant - at least this is the major assumption here. In that case (3) can be rephrased as follows:

\[
\hat{\phi}(n,p) = \psi_0(p) + k_q(n)q_p + k_d(n)d_p + \alpha(n) = \psi_0(p) + \psi_a(n).
\]  

(6)

The phase model of the imagettes stack has been split into two contributions: the intrinsic target phase, \( \psi_0(p) \), and the phase due to the optical path from imagette to the sensor, \( \psi_a(n) \).

The PS model in (6) is then written as follows:

\[
y(n,p) = a(n)\exp(j\psi_a(n)) \cdot b(p) \exp(j\psi_0(p)) + a(n)w(n,p) = \lambda \cdot u(n) \cdot v(p) + e(n,p).
\]  

(7)

where \( \lambda \) is a constant scaling and the noise term, \( e() \), has similar statistics as \( w() \), provided that data are coarsely normalized, say \( a(n) \approx 1 \).

**A. Fast estimation**

The separable model in (7) is suited to be inverted by the SVD of the data truncated at the first eigenvalue: the phases of the vector \( u(n) \) and \( v(p) \) provide the estimation of the optical paths and the target’s phase, respectively \( \psi_0(p) \) and \( \psi_a(n) \) in (6). Eckart–Young theorem ensures that the SVD is the optimal solution of (7) in L2 norm. However, the amplitude fluctuations in the small imagettes would potentially jeopardize the estimate, particularly when the imagette is small. As an example, in the case of a single bright pixel dominating over a dark background, the solution of (7) would align the phases of \( u(n) \) with those of the pixel, and the amplitude of \( v(p) \) would be zero everywhere, but for the index corresponding to that target. Thus we would get a small residual, and assume any bright target to be a PS.

To avoid this effect we normalize the complex data to have unitary modulus prior to the SVD. Thereafter, we perform PS detection as the event \( H_1 \) in the Generalized Likelihood Ratio Test (GLRT):

\[
\left| \frac{1}{N_I} \sum_{n=1}^{N_I} \exp \left( j(\hat{\phi}(n,p) - \hat{\phi}(n,p)) \right) \right| \leq \gamma_s \left| H_1 \right| (8)
\]

Detectors like (8) has been proposed by several authors, but the differences come indeed from the phase estimation, \( \hat{\phi} \), that is the crucial step [2], [3], [6].

One critical aspect in the detection is setting the proper threshold, that in our case depends upon the SNR, the window size, the number of images in the stack and the number of stable targets in the imagette. As our estimator is non-linear and rather complex to be studied by a mathematical model, we provide here results from numerical analysis made by assuming, as worst case condition, say \( N_I = 10 \) images, and \( N_{PS} = 2 \) and 3 stable targets in the imagette of \( N_P = 21 \) independent pixels. The missed detection and false alarm probabilities measured by Montecarlo simulation are plotted in Fig. 3 for different values of SNR, together with the probability of correct detection for different false alarm ratios. As the number of PS is much less than 10% of the pixels [15], thresholds \( \gamma_s > 0.7 \), and close to 0.8 should be chosen. Therefore we expect 10%-20% of the PS to be detected when two of them are in the imagette, whereas when three of them are there, the detection jumps to 80% if the quality is good (SNR=10 dB).
by averaging $N$ in Fig. III-A for different SNR and $N$ the threshold for 1% false alarms. The detection probability in the same conditions assumed as for in Fig. 3, and fixing algorithm is in the block diagram of Fig. 2. An evaluation of new estimation and detection step, by first nulling the most probability of correct detection as a function of the false alarm probability.

However even in that case the phase estimation would be quite effective in improving both detection and the phase accuracy, starting from say SNR $\sim 1$. Notice that the second iteration becomes quite effective in improving both detection and the phase estimation, starting from say SNR $\sim 3$ dB, and particularly for the case $N_{PS}=2$. The highest the SNR of the PS, the better the improvement.

![Figure 2. Two-steps algorithm for the PS detection and phase estimation.](image)

![Figure 3. Upper plots: probability of false alarms and missed detection as a function of the threshold in the case of $N_{PS}=2$ (left) and $N_{PS}=3$ PS (right) in a stack of $N_I=10$ imagettes of $N_P=21$ samples each. Lower plots: probability of correct detection as a function of false alarm probability.](image)

![Figure 4. Accuracy in the phase estimate and detection probability achieved at the first and the second step, i.e. after noise masking, assuming the same conditions as the previous figure. The dash-dot black line is the theoretical bound on $\sigma_\phi$ achievable for large SNR and exploiting $N_{PS}$ measures.](image)

### B. The multichannel case

The detection of coherent targets and the estimation of optical path here proposed is naturally suited to the extension to multichannel case, like for multi-polarization or multi-frequency. Eventually it would take advantage of independent measures, as a common optical path is expected.

As an example, in the full polarimetric case, the phase model (6) would be rearranged as follows:

$$
\begin{bmatrix}
    y_{HH}(n,p) \\
    y_{HV}(n,p) \\
    y_{VH}(n,p) \\
    y_{VV}(n,p)
\end{bmatrix} = \frac{1}{N} \sum_{i=1}^{N} (i\psi(n) + \psi(p)) + \frac{1}{N} \sum_{i=1}^{N} \psi(n) + \psi(p)
$$

where $\psi$ are the complex elements of the target scattering matrix. The model is still separable in $n$ and $p$, and can be rearranged as in (7). Detection and phase estimation would be done independently for each pixel in each polarization leading to the identification of stable signatures. This scheme is not an optimal detection for multi-polarimetric data, but is still provides a fast detection and phase estimation.

### C. Validation and comparison with the non-coherent detection

The coherent PS detection and phase estimation discussed so far has been tested with repeat-pass stacks from systems in C and X band, with different conditions of resolution, polarizations and baseline and Doppler Centroid span. The parameters of the datasets are summarized in Tab. I. The algorithm was reasonably fast, running in less than one hour for the largest stack of 17000×8000 samples ×43 images, on a dual-core laptop. This is much slower than the non-coherent detector proposed in [13] (that however does not estimate phases), but much faster and simpler than a full PS processor. Furthermore it does not rely on parametric models as for other phase-based detectors [6].

A consistence analysis was first made between the proposed approach and the non coherent detection based on the Dispersion Index (5). The cross-comparison between coherence and DI is shown in the bidimensional histogram of Fig. 5, for the ERS dataset of Flevoland. Notice that the most of the very best targets give consensus in the two indexes of quality: there is a minority of PS that are not detected basing on coherence, most likely are they are isolated. The reason why a minority
of PS is isolated, even though the PS are a small percentage of the pixels in the image (as it appears in the histogram), it that they are usually clustered like in constructions, rocks etc. This is indeed the reason why the proposed approach works, and, in practice gets good results with a limited effort.

On the other hand, there are many PS with high coherence, say $\gamma_s > 0.8$, that are not distinguishable by non-coherent detection, and this is a well known limitation for that detector.

Lacking a ground truth, we leave the visual inspection the role of evaluating the performances in a very critical case. The PS location superposed to the detected amplitude averaged over the $N_I=8$ polarimetric images of AgriSAR campaign is shown in Fig. 6 and refers to HH polarization. The threshold on coherence was much more restrictive than in rural areas much less PS are expected, and fewer images are given. The threshold on the non-coherent approach was forced to select the same number of PS, that is $N_p=680000$ in the frame of $\sim 25 \times 25$ km. Notice the clustering in the mad-made structures, like houses, village and along the railway, and the many false alarms of the non-coherent approach appearing as PS uniformly dispersed in agricultural fields.

The polarimetric case offer a further chance to confirm the quality of detected PS. In fact as a stable target should have a stable polarimetric signature in time. This condition can be checked by measuring the H-entropy, the dispersion of the eigenvalues, $\lambda$, of the coherency matrix[17]:

$$H = -\sum_{i=1}^{3} p_i \log_3 p_i \text{ where } p_i = \frac{\lambda_i}{\sum_{i=1}^{3} \lambda_i}$$

The trick is here to estimate the coherency matrix:

$$C = E \left[ k_p k_p^* \right] \text{ where } k_p = \begin{bmatrix} HH + VV \\ HH - VV \\ HV + VH \end{bmatrix}$$

Figure 6. Location of the PS detected by the non-coherent (left) and the proposed coherent approach (right) superposed on the detected amplitude of Barrax (Spain). Eight RADARSAT-2 full-polarimetric data, have been exploited, from AgriSAR campaign[16]. Results are for HH polarization. Thresholds were set to give the same number of PS (680000 in the $25 \times 25$ km frame of which a zoom is represented) in the two cases.
computational effort and complexity. We exploited the 41 ERS images of Milano datasets, and assumed as reference PS those with the coherence larger than 0.7. This set was compared with the results of both the proposed approach, and the non-coherent detection, applied to the full set of images and to a subset of $N_f=10$ images, chosen with good “quality” (as defined in section IV). The false alarm and correct decision probabilities (assuming the reference PS detected by the brute-force approach discussed), are plotted in Fig. 8 for the two detectors and the two sets of $N_f=41$ and $N_f=10$ images. In order to compare the two plots, the threshold for the non-coherent approach has been expressed in terms of the normalized index:

$$\gamma_n = \frac{1}{\sqrt{1 + \frac{1}{D^2}}}$$

that is directly matched to the complex coherence [12]. Here the false alarm is related to the total number of detected PS, therefore threshold should be tuned to get $\ll 50\%$ of wrong targets. This is achieved by assuming $\gamma_s > 0.75$, when the full set $N_f=41$ images is exploited, and $\gamma_s > 0.78$ for the reduced set of ten images. These values are consistent with those predicted in section III-A. Notice that setting the threshold for the non-coherent detector is much more critical, as small variations leads to quite different results.

The number of PS detected from the full set by the coherent approach is $<45\%$ of the good one, the limit being reached by accepting that half of those are false. The non-coherent approach performs better, detecting $<60\%$. Quite different results are obtained by limiting the stack to $N_f=10$ images, in which case $<38\%$ of the good targets are selected by the coherent approach and only $<18\%$ of the targets. We remark that this is a worst case of the proposed SVD-\(\gamma\) approach, due to the combination of large baseline span, large height dispersion in the urban area, and coarse resolution.

IV. INTERFEROMETRIC IMAGES QUALITY ASSESSMENT

The PS phases retrieved by (6) is suitable for estimating the coherence of each single image, or image block, in the same way we compute the PS coherence, (8), but transposing the

$$\gamma_f(n; b) = \frac{1}{N_{ph}} \sum_{p=1}^{N_{ph}} \exp \left( j (\hat{\phi}(n, p) - \tilde{\phi}(n, p)) \right)$$

where “b” identifies the block, and $N_{ph}$ the number of PS in the block. As the coherence is a very sensitive indicator of artifacts like misregistration, defocusing, geometric distortions and other errors [10], it is quite useful for automatic assessment of the interferometric image quality. However, there are two remarkable differences with respect to a conventional “master/slave interferometric coherence analysis”:

1) the coherence is here evaluated on each single image, versus the whole stack, and it is not related to a master (the master exists only to define the reference for coregistration)

2) the PS have been selected to be stable over the whole time and baseline span, thus coherence is minimally affected by temporal, space/volume decorrelation or other changes.

A demonstration is provided in the coherence maps in Fig. 9, measured on the basis of 50 $\times$ 50 blocks, selected to count at least 20 PS per block. The map on the left show a pretty high coherence for most of the PS blocks, despite the scene changes that we would expect from such winter image, with snow and freezing of the inner Zuiderzee sea at Flevoland, showing the robustness of this PS-based measure. Notice that decorrelation in a set of few blocks in the lower left of the figure where noise is most likely to come from very uncommon scene changes like snow, ambiguities or double reflection in the frozen sea.

In the image on the right, coherence has been measured after have intentionally introduced a shift of less than half a pixel in range in the lower half of the image. The decorrelation is quite appreciable. The block coherence is then a tool that could be used to estimate artifacts affecting to a portion of the image, like processor mosaiking errors, as well as strong atmospheric turbulence.

An example of the coherence measured on the ERS and COSMO Skymed (CSK) datasets is provided in Fig. 10. In
Coherence:

As a final example, the SVD-estimated phases and the low pass filtered phase residuals are shown in Fig. 11, for the mostly decorrelated image in Barcellona dataset ($\gamma = 0.93$). Notice that the phase, estimated at each imagette, captures the smooth contributions of the APS, as well as the uncompensated topography due to DEM and/or orbital errors. On the other hand the residual should be pure noise, however after low-pass filtering a topography correlated phase signature is found. This is a drawback of the imagette-wise estimator, that assume common topography to all PS in the cell. Notice that the impact is really small, as responsible for a phase standard deviation of 0.11 radians, that means $\gamma > 0.99$, whereas the measured coherence of 0.93 accounts for a much larger dispersion of $\sigma_\phi = \sqrt{-2\log(\gamma)} = 0.7$ radians. This supports the assumption of common optical path, as for the accuracy of the estimated phase.

V. CONCLUSION

We have proposed a novel coherent approach for the detection of stable targets the estimation of their phases in a stack of interferometric SAR images. The method has been designed for detecting Persistent Scatterers, therefore it is quite robust versus decorrelation, be it temporal or baseline-induced, and suited for few images, say ten or less. Its kernel is quite simple and efficient, as it bases on a two step iterated SVD performed on small overlapped imagettes. Extension to the multi-polarization case is straightforward, however in that case, the use of time-averaged entropy is recommended to enhance the PS detection.

The major limitation is in the assumption that nearby targets have the same phases in all the images: this has an impact on the number of PS, that depends on their distribution in the space, but not much on the phase quality. The estimated phases can then be exploited for coherent calibration [12], or for measuring the PS-coherence of each image or in blocks. Being sensitive to to artifacts in the whole acquisition and processing chain, mostly coregistration errors, but also block artifacts can be used for automated quality assessment of interferometric stacks. Results have been shown by real datasets, taken from ERS, CSK and RADARSAT II.

ACKNOWLEDGMENT

The work has been carried on with partial sponsoring by ASI - Agenzia Spaziale Italiana, in the framework of the project #1080 "SAR data Calibration and Validation by Natural Targets": raw CSK datasets have been provided by ASI AgriSAR RADARSAT-2 data have been provided by the European Space Agency in cooperation with MacDonald Dettwiler under the framework of AgriSAR 2009 campaign. ERS datasets have been provided by ESA. The authors thanks Aresys for processing and co-registering the data stacks and L. Iannini for the figures.

Figure 9. Superposition of the averaged amplitude and the proposed PS-based block coherence (color-scale) on two images of ERS stack over Flevoland. Left: acquisition in data 22-12-95: the PS-coherence is high and uniform in all the blocks despite the unusual scene with freeze and snow over the Zuiderzee sea. Right: the decorrelation evident in the lower half image is due to a coregistration error that has been intentionally introduced.

Figure 10. Average image coherence and Doppler Centroid for Flevoland (left) and CSK (right) estimated over 140000 PS in both cases. The three CSK sensors are represented with different colors and markers.

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Figure 11. Left estimated phase of Barcellona dataset, referred to the HH image in date 9-3-2010, with the worst coherence, $\gamma = 0.93$, superposed to the mean amplitude. The major contribution is due to DEM error, due to the use of preliminary orbits. The residual phase, low-pass filtered, is on the right. It should be pure noise, instead there are some topography-related features due to the intrinsic limitation in processing nearby targets (see Fig. 1). However notice that the phase standard deviation is quite small, 0.11 radians, corresponding to 1% coherence loss.
for the polarimetric analysis. Last, but no least, the authors
thanks anonymous reviewer for their constructive criticism.

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