DARIS (DEFORMATION ANALYSIS USING RECURSIVE INTERFEROMETRIC SYSTEMS) A NEW ALGORITHM FOR DISPLACEMENT MEASUREMENTS THROUGH SAR INTERFEROMETRY

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ABSTRACT

In the present work we describe a new and alternative repeat-pass interferometry algorithm designed and developed with the aim to: i) increase the robustness wrt to noise by increasing the number of differential interferograms and consequently the information redundancy; ii) guarantee high performances in the detection of non linear deformation without the need of specifying in input a particular cinematic model. The starting point is a previous paper [4] dedicated to the optimization of the InSAR coregistration by finding an ad hoc path between the images which minimizes the expected total decorrelation as in the SABS-like approaches [3]. The main difference wrt the PS-like algorithms [1],[2] is the use of couples of images which potentially can show high spatial coherence and, which are neglected by the standard PSI processing. The present work presents a detailed description of the algorithm processing steps as well as the results obtained by processing simulated InSAR data with the aim to evaluate the algorithm performances. Moreover, the algorithm has been also applied on a real test case in Poland, to study the subsidence affecting the Wieliczka Salt Mine. A cross validation wrt SPINUA PSI-like algorithm [5] has been carried out by comparing the resultant displacement fields.

1. INTRODUCTION

In the last decade many algorithms which perform repeat-pass interferometry have bee developed and applied to study different geophysical phenomena. These algorithms can be clustered into two classes according to the strategy adopted for coupling the images. The Persistent Scatterers Interferometry (PSI) approach [1], which studies the phase information over single isolated objects characterised by a high temporal phase stability; this approach is usually implemented by computing interferometric fringe pairs for all the acquisitions w.r.t. the same reference master image, then performing advanced phase analysis on the pixels exhibiting stable SAR response throughout the stack. The second class of algorithms exploits differential interferograms obtained by applying the standard differential interferometry processing to small baseline acquisition subsets (the so-called SBAS approach [3]). The constrains on both spatial and temporal baseline values provide interferometric pairs with low decorrelation thus making feasible the phase unwrapping and the identification of regions with relative high coherence values. Different implementations of these two approaches to repeat-pass interferometry have been proposed and applied to many test cases. The complicated aspect in both the above-mentioned multi-temporal data processing approaches is the need of joint non-linear estimation of stochastic fields due to atmospheric signal, deformation and errors in the reference DEM. In summary, the atmospheric phase screen estimation can be performed thanks to its stochastic [6] behaviour which is known to be totally uncorrelated in time but correlated in the space domain, with a power-law spatial frequency spectrum. The case of the displacement fields is much more complicated, since these are expected to have certain correlation properties both in time and space. Moreover, a reliable discrimination of the two types of contribution requires careful consideration of both signals’ characteristics, such as typical spatial-temporal scales, etc.

In the present work we describe a new and alternative repeat-pass interferometry algorithm designed and developed with the aim to: i) increase the robustness wrt to noise by increasing the number of differential interferograms and consequently the information redundancy; ii) guarantee high performances in the detection of non linear deformation without the need of specifying in input a particular cinematic model. The last issue is crucial in particular when dealing with end user applications dedicated to the monitoring of phenomena like landslides as well as stability of man made structures (buildings, bridges, …) which show non linear evolution (often approximated with a step linear cinemetic).

In section 2 we presents the algorithms introducing to the main processing steps. Section 3 provides a first evaluation of the algorithm performances obtained by using DInSAR stacks ad hoc simulated. Finally, the application on a real test case is presented in section 4 with a cross comparison wrt SPINUA PSI-like
2. ALGORITHM DESCRIPTION

The DARIS (Deformation Analysis using Recursive Interferometric Systems) algorithm is aimed at inferring ground deformation through the analysis of multi-temporal satellite SAR acquisitions. As already said, the proposed processing strategy is aimed at increasing the information redundancy w.r.t the standard PSI for more robust estimation, as well as at detecting non linear deformations without the need of input models.

The algorithm, starting from a previous work [4], follows an approach close to the SBAS technique [3].

A flow chart of the DARIS processing chain is sketched in Fig. 1. The algorithm is composed by standard DInSAR pre-processing followed by three main processing steps which perform the multi-temporal analysis.

2.1. Pre-processing

Once a dataset of SAR images is available, the selection of the interferometric couples is carried out by using a proper distance \( D \) [4] defined as function of the geometrical \( (b_\perp) \) and temporal baselines \( (b_t) \). According to a constrain on the maximum value of \( D \), a graph \( G \) is generated in the space defined by \( (b_t, b_\perp) \). This constrain guarantees relatively high values of spatial coherence and consequently favourable condition for phase unwrapping.

On the top of fig. 2, as an example, it is sketched, a graph relative to a real dataset composed by 39 ERS-1/2 SAR and detailed in section 4. In this case a simple Euclidean distance has been used for \( D \). The constraint imposed for the graph generation is: \( b_t < 1100 \) d, \( b_\perp < 350 \) m.

According to the graph connections, a stack of unwrapped differential phase fields \( (\Phi_{m,s}) \) are generated all resampled to a unique geometry. The table on the bottom of fig. 2 lists the interferograms sorted according to increasing acquisition times of the master images, \( t_m \).

The set of these acquisition times, \( M_t = \{t_m\} \), defines the sampling space of the deformation to be retrieved. In the present case 156 interferograms were generated corresponding to 38 different \( t_m \).

Before phase unwrapping, a smoothing filter is applied on the DInSAR phase field to increase the Signal to Noise Ratio (SNR) thus making more robust the unwrapping procedure.

2.2. Smooth model

This step provides for each pixel and for each acquisition time \( t_m \), a first estimation of the deformation obtained through a Least-Square solution of a linear system in the hypothesis of linear cinematic. This first coarse estimation is functional to the further processing step which is devoted to filter out the atmospheric signal.

More in detail, defined a reference time \( t_0 \) and an acquisition time \( t_s \in M_t \), a system of equations \( S_i \) is built by involving all the interferograms in the reference graph generated by coupling images within a time interval \( I_s = [t_0, t_s] \). The set master and slave couples used is \( i_s = \{(m,s) \in G \mid t_m \in I_s \land t_s = t_m \} \).

A linear model is assumed for the deformation, thus the DInSAR phase results:
The system of equation can be written as:

\[ S_x : \{ T_x, B_x \} \cdot \bar{X}_x = \bar{\Phi}_x \]  

where, \( \bar{\Phi}_x \) is the column vector of the unwrapped interferometric phases, \( T_x \) is the column vector of the temporal baselines, \( B_x \) is the column vector of the coefficients multiplying \( \Delta z_x \) in eq. (1) and, \( \bar{X}_x \) is the vector of the unknowns \( \bar{v}_x \) and \( \bar{\phi}_x \). This system refers to a single pixel in the image and provides the solution for the time \( t_x \) in \( M_x \).

The systems \( \{ S_x \} \) have rank < 3 thus allowing a Least Square solution. Moreover, since they are independent, the solutions can be computed in parallel.

The output of this processing step is a first coarse evaluation of the deformation in the hypothesis of linear periodic variation of the mean velocity, \( \bar{v}_x \), and the look angle relative to the master view. The evaluation of the deformation values varying monotonically. This particular choice avoids to filter out possible high temporal frequency in the deformation. The previous processing, provides a first coarse estimation of the deformation thus allowing to sort the interferometric phase according to increasing deformation values.

In fig. 3 we provide an example of the procedure obtained by using data simulated according to the configuration detailed in fig. 2. Image (a) represents the estimated phase values which account for deformation estimated through the smooth model, \( \Phi_{ms}^{smooth} \), and sorted according to increasing values. Image (b) shows original interferometric phases ordered according to increasing value of \( \Phi_{ms}^{smooth} \). The result of filtering is represented in green in the image (c).

### 2.4. Fast model

This processing step performs for each acquisition time \( t_x \), the estimation of the deformation by using a third order cinematic model:

\[
\Phi_{fast}^{sm} = \Phi_{ms}^{fast} - \Phi_{ms}^{fast} = [\bar{v}_x \cdot (t_m - t_0) + \frac{1}{2} \bar{a}_x \cdot (t_m - t_0)^2 + \frac{1}{6} \bar{\Delta a}_x \cdot (t_m - t_0)^3] - [\bar{v}_x \cdot (t_x - t_0) + \frac{1}{2} \bar{a}_x \cdot (t_x - t_0)^2 + \frac{1}{6} \bar{\Delta a}_x \cdot (t_x - t_0)^3]
\]

where \( \bar{v}_x \) is the mean velocity, \( \bar{a}_x \) is the mean acceleration and \( \bar{\Delta a}_x \) the variation of the mean acceleration. As for the smooth model processing, a system of equation is defined for each \( t_x \):

\[ F_x: \bar{T}_x \cdot \bar{X}_x = \bar{\Phi}_x \]

where \( \bar{T}_x \) is the column vector which provides the phase values measured at \( \Phi_{ms}^{fast} = \Phi_{ms}^{DEMs} - \Phi_{ms}^{DEMs} \), \( \bar{X}_x \) is the vector of the unknowns \( \bar{v}_x \), \( \bar{a}_x \) and \( \bar{\Delta a}_x \), and \( \bar{T}_x \) is defined as:

\[ \bar{T}_x = \begin{pmatrix}
(t_{a1} - t_{c1})^2 -(t_{a1} - t_{c1})^2 & (t_{a1} - t_{c1})^2 -(t_{a1} - t_{c1})^2 \\
(t_{a2} - t_{c2})^2 -(t_{a2} - t_{c2})^2 & (t_{a2} - t_{c2})^2 -(t_{a2} - t_{c2})^2 \\
... & ...
\end{pmatrix}
\]

Of course, this system refers to a single pixel in the image and provides the solution for the time \( t_x \) in \( M_x \). The considerations relative to \( I_x \) already provided in section 2.2, hold also in this case. Since the deformation parameters are estimated for each time acquisition \( t_x \) and by using a third order cinematic model the algorithm results robust in measuring non-linear deformations.

\[ F_x: \bar{T}_x \cdot \bar{X}_x = \bar{\Phi}_x \]
Also in this case the systems \{F_x\} have rank \(< 3\) thus allowing a Least Square solution. The method is robust wrt the presence of disjoint subsets of images since it allows to infer deformation values without the need of Singular Value Decomposition for solving the system of equations.

Finally, the systems are independent and can be solved in parallel.

### 2.5. Pixel selection

Once the deformation has been estimated for each pixel through the fast model, a further step is required which select coherent pixels. This selection is performed according to the so-called temporal coherence defined as:

\[
γ_t(p) = \frac{1}{N_t} \sum_{j=1}^{N_t} e^{j[Φ_{s_{def}}^t(p) - Φ_{s_{def}}^t(p - 1) - Φ_{s_{DEM}}^t(p) - Φ_{s_{APS}}^t(p)]} \quad (6)
\]

where \(Φ_{s_{def}}\) depends on the deformation estimated through the fast model, \(Φ_{s_{DEM}}\) depends on the residual topography computed by relation (3) and, \(Φ_{s_{APS}}\) depends on the atmospheric component estimated through the HP filter in section 2.3.

The temporal coherence is designed to select those pixels where both, the corresponding targets on the ground behaves coherently during the observation and, the cinematic model adopted allows to properly estimate the actual deformation. The selection is performed according to a threshold:

\[
P_{th} = \{p \mid γ_t(p) \geq γ_{th} \}
\]

For pixels in \(P_{th}\) the whole deformation, the residual topography and, the displacement trend along time are available.

The final spatial resolution depends on the spatial filtering applied before phase unwrapping to increase the phase SNR.

### 3. ALGORITHM PERFORMANCES IN SIMULATION

The performances of the algorithm have been tested by using a simulation framework. Different deformation models, power values of the atmospheric signal, residual topography values and random noise power levels have been combined to generate stacks of simulated absolute differential phase fields:

\[
Φ = Φ_{s_{def}} + Φ_{s_{DEM}} + Φ_{s_{APS}} + Φ_{noise} \quad (7)
\]

Both linear and non linear models have been adopted to simulate the deformations. Particular attention has been devoted to step linear trends which can play a crucial role when dealing with phenomena like landslides as well as with the stability of man made structures (buildings, bridges, …). Concerning the atmospheric contribution to the InSAR phase, it has been simulated according to the well known spectral behavior [6] and by using different values of signal power up to \(Φ_{s_{APS}} \in [-3π, +3π]\). The \(Φ_{s_{DEM}}\) has been simulated by assuming a random spatial distribution of the residual topography \(Δz\) ranging from -10 m and 10 m. Finally, the \(Φ_{noise}\) has been simulated as gaussian noise with different values of standard deviation, \(σ_n\), up to \(π/2\).

The DInSAR phase stacks have been simulated by using the temporal and geometrical baselines of a real dataset of 39 ERS-1/2 acquisition detailed in section 4.

Different graphs have been simulated in order to verify how the number and the distribution of the interferograms involved in the processing, impact on the final estimation. In the following we present the results obtained by using the graph in fig. 2.

In fig. 4 we show in red the simulated deformation trend and in blue the deformation inferred through DARIS for different cinematic models and for \(Φ_{s_{APS}} \in [-π, +π]\).
and $\sigma_n = \pi/6$. The algorithm is able to follow properly non linear trends and in particular the step linear behavior on the left bottom of the figure. It is worthwhile to point out that in this case the change in the linear regime occurs close to the beginning of the observation interval and thus only few acquisitions are available before the simulated event.

The global performances of the algorithm have been evaluated by analyzing the distribution two figures: the temporal coherence defined by relation (6) and, the mean difference between the simulated and estimated deformation values:

$$
\mu_s(p) = \frac{1}{N_s} \sum_{s=1}^{N_s} \left| \text{def}_s^\text{sim}(p) - \text{def}_s^\text{est}(p) \right|
$$

Figures 5 and 6 show the distributions of $\gamma$ and $\mu_s$, respectively, for different values of atmospheric contribution and noise levels. The images at the top of the figures refer to $\Phi^\text{APS} = 0$ while those on the bottom refer to $\Phi^\text{APS} \in [-2\pi, 2\pi]$. The colour of the beams depends on the $\sigma_n$ which ranges from 0 to $\pi/2$ (see legend).

The values $\gamma$ and $\mu_s$ are divided by the maximum of the distribution and expressed in percentage. In order to guarantee the statistical confidence, for each configuration ($\sigma_n$, $\sigma_{APS}$) the distribution has been obtained by repeating the estimation on phase stacks simulated by generating randomly, different atmospheric fields and noise fields.

Of course the performance of the algorithm worsen as the atmospheric contribution and the power of noise increases. This first implementation of the algorithm seems to be quite robust against noise level. The quality of the results seems so be partially conditioned by the power of the atmospheric signal.

4. APPLICATION ON A REAL DATASET

The algorithm has been also tested by using satellite SAR data acquired in Poland over the Wieliczka salt mine (see fig. 7). The deformation map provided by DARIS has been compared wrt the one obtained through the SPINUA [2] PS-like algorithm which in turn was already validated with the help of geological experts [5]. The selected dataset consists of 39 ERS-1/2 descending acquisitions (track 179, frame 2601) and covers a period from 1992 to 2000. The frame coverage is sketched in fig. 7.

Wieliczka, a town located 14 km SE of Cracow, is home to a unique salt mine, over 700 years old, one of the best known tourist attractions in Poland. Each year the mine is visited by about 1 million tourists from all over the world and in 1978 UNESCO placed it on its first International List of the World Cultural and Natural Heritage. First PSI analysis on this area has been already derived [5] by processing, through the PSI SPINUA technique [2], the same ERS dataset. Numerous radar targets (over 100 PS/km²) have been identified, allowing ground motion monitoring in the Wieliczka area (see fig. 8). In particular, the results showed the presence of continuous subsidence with average movements ranging from about 1 to 2 cm/yr in the period 1992-2000. The detected width of the subsiding zone corresponds very well to the extent of the underground salt mine [5], whereas its length (around 4.5 km) is somewhat shorter with respect to that of the mining works and of the known salt deposit.

The DARIS algorithm has been applied to same dataset. Before selecting the radar images we examined historical precipitation records of the Wieliczka meteorological station. This was done to avoid ordering images acquired on days with significant snow cover or heavy snow/rain precipitations. The reference topography was provided by an external SRTM-derived DEM with spatial resolution of 90x90 m². Differential interferograms of the Wieliczka test site have been generated according to a graph generated by using the following constraint: $b_1 < 780 \text{ d}$, $b_2 < 200 \text{ m}$. The differential phase fields have been spatially averaged by using a kernel size of 21 sample in azimuth and 5 in range, then phase unwrapping has been performed through the SNAPHU algorithm [7]. Once the DInSAR phase stack was available, the DARIS algorithm has been applied to select coherent pixels and generate displacement values and residual topography.

In fig. 9 the mean deformation map for $\gamma_{\text{ref}} = 0.75$ is represented over an optical image provided by Google-Earth™. DARIS is able to identify and to measure the subsiding area although the resultant deformation map shows a lower spatial resolution than the one provided by SPINUA which processes single look data. Anyway, the two deformation patterns result very similar.

![Figure 4. Simulated (red) and estimated (blue) deformation trends for $\Phi^\text{APS} \in [-\pi, +\pi]$ and $\sigma_n = \pi/6$.](image-url)


5. CONCLUSIONS

The paper presents a new and alternative repeat-pass interferometry algorithm designed and developed with the aim to: i) increase the robustness wrt to noise by increasing the number of differential interferograms and consequently the information redundancy; ii) guarantee high performances in the detection of non-linear deformation without the need of specifying in input a particular cinematic model.

The algorithm has been described and tested on both simulated and real dataset. In particular it has been verified that the algorithm is able to identify and measure non-linear deformations and performs robustly wrt different values of phase noise.

The main difference wrt other algorithms consists in estimating the deformation independently for each acquisition time $t_x$ and, by involving a number of interferograms which depends on both the graph which defines the connection between the images and, the time interval $I_x$ selected for the estimation. By setting properly the interval $I_x$, a third order cinematic model provides reliable estimation of non-linear deformation. Further developments are in progress in order to: i) make the technique robust wrt PU errors which can arise in particular where low coherence areas are present; ii) use the spatial gradient of the phase instead of the absolute values; iii) merge together this algorithm with a PSI-like approach (SPINUA).

The algorithm will be applied also in the framework of MORFEO project for slope instability monitoring.
where, step linear deformation trends (as those investigated in simulation) can be of interest for revealing failure processes.

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7. REFERENCES


