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A Synergy Method to Improve Ensemble Weather Predictions and Differential SAR Interferograms

Franz-Georg Ulmer *, Nico Adam

Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Methodik der Fernerkundung, Münchener Straße 20, 82234 Weßling, Germany

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ABSTRACT

A compensation of atmospheric effects is essential for mm-sensitivity in differential interferometric synthetic aperture radar (**DInSAR**) techniques. Numerical weather predictions are used to compensate these disturbances allowing a reduction in the number of required radar scenes. Practically, predictions are solutions of partial differential equations which never can be precise due to model or initialisation uncertainties. In order to deal with the chaotic nature of the solutions, ensembles of predictions are computed. From a stochastic point of view, the ensemble mean is the expected prediction, if all ensemble members are equally likely. This corresponds to the typical assumption that all ensemble members are physically correct solutions of the set of partial differential equations. DInSAR allows adding to this knowledge. Observations of refractivity can now be utilised to check the likelihood of a solution and to weight the respective ensemble member to estimate a better expected prediction.

The objective of the paper is to show the synergy between ensemble weather predictions and differential interferometric atmospheric correction. We demonstrate a new method first to compensate better for the atmospheric effect in DInSAR and second to estimate an improved numerical weather prediction (**NWP**) ensemble mean. Practically, a least squares fit of predicted atmospheric effects with respect to a differential interferogram is computed. The coefficients of this fit are interpreted as likelihoods and used as weights for the weighted ensemble mean. Finally, the derived weighted prediction has minimal expected quadratic errors which is a better solution compared to the straightforward best-fitting ensemble member. Furthermore, we propose an extension of the algorithm which avoids the systematic bias caused by deformations. It makes this technique suitable for time series analysis, e.g. persistent scatterer interferometry (**PSI**). We validate the algorithm using the well known Netherlands-DInSAR test case and first show that the atmospheric compensation improves by nearly 40% compared to the straightforward technique. Second, we compare our results with independent sea level pressure data. In our test case, the mean squared error is reduced by 29% compared to the averaged ensemble members with equal weights. An application demonstration using actual Sentinel-1 data and a typical test site with significant subsidence (Mexico City) completes the paper.

1. Introduction

Synthetic aperture radar (**SAR**) is a popular remote sensing technique to observe the topography of the earth and its millimetre displacements. The strength of a signal which is scattered back is independent of the actual weather condition. However, the wave propagation velocity depends on water vapour, pressure and temperature (see Smith and Weintraub, 1953).

Differential interferometric synthetic aperture radar (**DInSAR**) images are subtracted phase information of two SAR acquisitions, corrected for topography, and are therefore affected by atmosphere. In order to allow precise interferometric measurements, the atmospheric effect needs to be compensated and is known as atmospheric phase screen (**APS**). Currently, the time series analysis using large stacks of SAR data is well established. Essentially, it is based on the uncorrelated atmosphere with respect to time requiring a long time series (see Ferretti et al., 2001). Different authors have successfully demonstrated the mitigation of the APS using NWP, for example (Holley et al., 2007; Jung et al., 2014; Nico et al., 2011; Adam, 2013; Pierdicca et al., 2011; Perissin et al.,

* Corresponding author.
E-mail addresses: Franz-Georg.Ulmer@dlr.de (F.-G. Ulmer), Nico.Adam@dlr.de (N. Adam).

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2011). These papers show that the hydrostatic component can be estimated using NWP models. However in practice, the wet-delay is more difficult to reproduce using numerical weather prediction (**NWP**) due to its turbulent nature. For the second application, i.e. improved numerical weather prediction (Pichelli et al., 2015) have demonstrated a better forecast for weak to moderate precipitation.

NWP implements a set of partial differential equations (**PDEs**). The solution can never be precise due to model or initialisation uncertainties. In practice, the initial atmosphere state data are spatially undersampled and affected by measurement errors. Additionally, different options (e.g. resolution, size of simulated area, physics options and integration time step length) result in different valid (i.e. physically correct) solutions of the PDEs (Liu et al., 2011). Another effect results from error propagation. Imprecise convection strength causes timing deviations. As a result, humidity is dislocated with time of day.

Epstein (1969) proposed a stochastic dynamic model (i.e. ensembles of PDEs solutions) to handle uncertainties produced by the weather prediction model or the initialisation data. An ensemble represents likely atmospheric states and it spreads the uncertainties. It is a well established practice to use independent atmosphere state observations e.g. sounding, lidar and weather stations. Hence, ensemble members can be verified by such observations. A straightforward approach is to use only the most likely (best fitting) ensemble member. Another method linearly combines the ensemble members. The second tactic allows a better fit of the prediction to the practically observed data. However, this improvement can only be ensured at the measurement location. In other areas, over-fitting can occur. We demonstrate the use of DInSAR data as independent atmosphere measurements avoiding over-fitting. The improvement is based on the high resolution and sensitivity as well as the large spatial coverage of the radar data.

In particular, DInSAR data provide indirect measurements of pressure, temperature and humidity which are projected into SAR geometry and mapped into delay measurements physically related to refractivity. For this reason, the ensemble members can be assessed regarding their likelihood of occurrence. Instead of the straightforward best-fitting ensemble member, the weighted ensemble mean provides the final atmosphere hindcast.

For n ensemble members $F = \{f_1, \ldots, f_n\}$,

$$\mathrm{WEM}(F) = \sum_{i \in \{1,\ldots,n\}} a_i f_i \tag{1}$$

the weighted ensemble mean (**WEM**) with weights (likelihoods) $a_i \in \mathbb{R}_+$ and $\sum_{i\in\{1,\ldots,n\}} a_i = 1$ equals the expected value. In addition, the mass conservation can be relaxed to $\sum_{i\in\{1,\ldots,n\}} a_i \approx 1$ (R. Bamler, personal communication 4 May 2015). As a consequence, the estimated prediction can be improved in case of biased (i.e. physically incorrect) solutions.

The objective of the actual work is to present a framework which produces synergy between ensemble weather predictions and DInSAR measurements. It means both benefit from each other.

2. Methods

The APS (ϕ'_a) is composed of a hydrostatic term corresponding to (refractivity N_h) and a wet term corresponding to (refractivity N_w). Both are influenced by temperature (T). The hydrostatic term is additionally influenced by total pressure (P) while the wet term is influenced by water vapour (e). Based on physics, the range distance deviation is defined by

$$\phi'_a = 10^{-6} \int_{\vec{\boldsymbol{p}}_{(i,j)}}^{\vec{\boldsymbol{s}}} N(\vec{\boldsymbol{v}}) \mathrm{d}\vec{\boldsymbol{v}} \tag{2}$$

where

$$N = \underbrace{K_1 \frac{P}{T}}_{N_h} + \underbrace{K_2 \frac{e}{T} + K_3 \frac{e}{T^2}}_{N_w}. \tag{3}$$

$\vec{\boldsymbol{p}}_{(i,j)}$ is the three dimensional location on Earth of the actual DInSAR pixel and $\vec{\boldsymbol{s}}$ is the position of the SAR-satellite. Eq. (3) models the refractivity (N) and the coefficients (K_1, K_2, K_3) are provided by Rüeger (2002). Practically, for every pixel of the SAR-image, integration through the predicted three dimensional atmospheric state produces an APS (ϕ'_a) candidate. A differential interferogram is composed of two SAR acquisitions. Of course, the corresponding APSs are needed for both acquisition times (τ_1, τ_2). From ensemble members and corresponding delays for both dates, candidates of APSs are computed ($\phi'_a(\tau_1, \cdot), \phi'_a(\tau_2, \cdot)$). A convex optimisation computes a least norm fit of the NWP data matrix $\mathbf{A}$ with respect to the DInSAR observation ($\phi_I(\tau_1, \tau_2)$) with $r \times c$ pixels:

$$\text{minimise}: \quad ||r_k||_2 \tag{4}$$

subject to:

$$r_k = \left(\mathbf{A}a - \hat{\phi}_I(\tau_1, \tau_2)\right)_k \text{ for } k \in \{1, \ldots, rc\} \tag{5}$$

$$\sum_{k=1}^{n_{\tau_1}} \boldsymbol{a}_k = 1, \tag{6}$$

$$\sum_{k=n_{\tau_1}+1}^{n_{\tau_1}+n_{\tau_2}} -\boldsymbol{a}_k = 1, \tag{7}$$

$$\sum_{k=1}^{rc} A_{k,i} = 0 \text{ for } i \in \{1, \ldots, n_{\tau_1} + n_{\tau_2}\}, \tag{8}$$

$$\sum_{k=1}^{rc} \left(\hat{\phi}_I(\tau_1, \tau_2)\right)_k = 0. \tag{9}$$

where $n_{\tau_1},\ n_{\tau_2}$ are the counts of ensemble candidates. The last two constraints cope with the unknown interferometric phase offset. Practically, coefficients (a_i) of best-fitting linear combination are interpreted as likelihoods. In doing so, the WEM equals the expectation ($\mathrm{E}\{\cdot\}$) definition in a stochastic meaning. Therefore, the WEM equals the centre point of all predictions, such that the expected quadratic error is minimal.

2.1. Model of atmospheric phase screen approximation and algorithm

The starting point is an absolute DInSAR phase $\phi : \mathbb{N} \mapsto \mathbb{R}^{r\times c}$ at acquisition time τ with r rows and c columns (see Kampes, 2006):

$$\phi(\tau) = \phi_a(\tau) + \phi_d(\tau) + \phi_n(\tau) \tag{10}$$

$\phi_a,\ \phi_d$ and $\phi_n : \mathbb{N} \mapsto \mathbb{R}^{r\times c}$ are the phase delays caused by the atmosphere, the deformation and noise, respectively.

An interferometric phase $\phi_I : \mathbb{N}^2 \mapsto \mathbb{R}^{r\times c}$ is defined by:

$$\phi_I(\tau_1, \tau_2) = \phi(\tau_1) - \phi(\tau_2) + \mathbf{O} \tag{11}$$

where $\mathbf{O}$ is a matrix (image) modelling the unknown interferometric phase offset. We assume that the atmosphere effect is statistically dominant compared to the deformation and the noise. Let $\phi'_a(\tau, k) : \mathbb{N}^2 \mapsto \mathbb{R}^{r\times c}$ be the k'th predicted APS candidate of a single SAR acquisition. Similar to the weighted ensemble mean, the corresponding APS candidates are weighted to approximate the SAR acquisition's atmosphere $\phi_a(\tau)$.

$$\phi(\tau) \approx \overbrace{\left(\sum_{k=1}^{n} a_\tau(k) \phi'_a(\tau, k)\right)}^{\approx \phi_a(\tau)} \tag{12}$$