FEASIBILITY OF RETRIEVING SPATIAL VARIATIONS OF ATMOSPHERIC PHASE SCREEN AT EPOCHS OF SAR ACQUISITIONS FROM SAR INTERFEROMETRY

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ABSTRACT

In this paper, we consider the atmospheric phase screen (APS) observed by SAR Interferometry (InSAR) as a valuable source for atmospheric studies and propose an approach to infer its spatial variations at the epochs of SAR acquisitions from a set of interferograms. Our approach is applicable to cases in which land deformation in the area of interest is negligible during the SAR acquisitions or the deformation signal is known and can be subtracted from the interferometric phases. The approach uses a spatio-temporal network formed by small-baseline interferograms to estimate APS spatial variation at each SAR acquisition by means of constrained least-squares adjustment. We applied the approach to 40 interferograms formed by 22 ASAR images acquired by Envisat in descending orbit over a scene from south-west Australia. The estimated APS spatial variations during the 22 SAR acquisitions are evaluated based on the analyses of estimation bias, power spectral density and temporal correlation. In addition, we cross validate some of the APS estimates for dates on which cloud free MERIS integrated water vapor (IWV) measurements are available. Finally, we conclude that it is feasible to retrieve APS spatial variations at the epochs of SAR acquisitions provided that the number of SAR images used for retrieving is sufficiently large and decorrelation noise, i.e. geometric and temporal decorrelation, does not obscure the atmospheric signal in the interferograms.

Key words: InSAR, water vapor, atmospheric phase screen (APS).

1. INTRODUCTION

Over the last two decades, great achievements of spaceborne SAR Interferometry (InSAR) for Earth observation have been widely witnessed. Most of its applications can be found in the fields of ground deformation monitoring and land topography modeling. In these applications the atmospheric phase screen (APS) is commonly regarded as a phase noise with high spatio-temporal variations caused by water vapor in the lower part (< 2 km) of the troposphere. On the other hand, it has been demonstrated that InSAR can provide high spatial resolution measurement of APS spatio-temporal variations [HWZK99] [Han01], provided that the ground deformation is negligible and an external DEM model is available to compensate the topographic phase contribution. However, comparing to the spatio-temporal variations of APS, its spatial variations at the epochs of SAR acquisitions are apparently more valuable for atmospheric studies such as climate studies, mesoscale meteorology and numerical forecasting. Therefore, for InSAR to be used as a tool for the atmospheric studies we need be able to retrieve the APS spatial variation at each SAR acquisition. Based on this motivation we develop an approach to estimate APS spatial variations at the epochs of SAR acquisitions from a set of small-baseline interferograms. Our approach is applicable for cases in which land deformation in the area of interest is negligible during the SAR acquisitions or the deformation signal is known and can be subtracted from the interferometric phases. The paper is organized as follows. In section 2 the developed approach, including network forming, variance component estimation, outliers detection, spatial filtering and interpolation by kriging, is discussed in detail. In section 3 a case study is carried out to evaluate the approach. The area chosen for the case study is located in south-west Australia. In total, APS spatial variations at the epochs of 22 SAR acquisitions are estimated from a network formed by 40 interferograms. In addition, the estimated APS spatial variations are validated internally by means of estimation bias, power spectral density and temporal correlation. For external validation we compare the APS estimates to the MERIS water vapor measurements acquired under cloud free condition. Finally, discussion and conclusion are given in section 4.
Figure 1. Baseline-Network plot of SAR acquisitions. Horizontal-axis: temporal baseline; Vertical-axis: perpendicular baseline. Each node represents an acquisition and each edge connecting two nodes represents an interferogram formed by the two acquisitions. Dashed edges are the ones which cannot be included in the closed loop of the network due to baseline constrains.

2. ALGORITHM

2.1. Forming network and APS estimation

Given \( N+1 \) SAR acquisitions we can form \( N(N+1)/2 \) different interferograms from them, although only \( N \) of these interferograms are independent. For repeat-pass interferometry, baseline constrains (e.g. \( B_{pp}<500 \) m, \( B_t<180 \) days depending on the sensors and areas of interest) are necessary in order to suppress decorrelation noises [ZV92][GMGP+94]. Under the baseline constrains, the number of interferograms that can be formed is reduced substantially and their baseline plot would look similar to the spatio-temporal network sketched in Fig.1. For an arbitrary pixel \( p \) in the aligned interferograms (i.e. coregistrated with respect to a common acquisition geometry) in the network, its unwrapped interferometric phases can be written as:

\[
\phi^i_p = \phi^i_{\text{aps}} + \phi^i_{\text{orb}} + \phi^i_{\text{defo}} + \phi_{\text{topo}} + \phi_{\text{noise}},
\]

where \( \phi_{\text{aps}}^i \) is the difference of the APS disturbances between acquisitions \( i \) and \( j \); \( \phi_{\text{orb}}^i \) represents the phase caused by the errors in the orbit determination; \( \phi_{\text{defo}}^i \) counts for the land deformation during the acquisitions and \( \phi_{\text{topo}} \) denotes the phase contribution from local surface topography; \( \phi_{\text{noise}} \) is the noise term including decorrelation noise, coregistration/resampling noise, etc. The deformation term can be ignored for stable ground surfaces. The topography contribution can be compensated by a global DEM (e.g. SRTM) and the orbit error can usually be modeled as a surface trend [Han01] and then subtracted from the unwrapped phase. Therefore Eq.(1) can be reduced to:

\[
\phi^i_p = \phi^i_{\text{aps}} - \phi^i_{\text{aps}} + \phi_{\text{noise}},
\]

which can be written in a matrix form:

\[
y_p = Ax + e,
\]

where \( y \) is a \( m \times 1 \) observation vector which contains the unwrapped interferometric phases at the pixel \( p \) and \( m \) is equal to the number of interferograms in the network; \( x \) is a \( n \times 1 \) parameter vector which contains the unknown APS at the epochs of SAR acquisitions and \( n \) is the number of the SAR acquisitions from which the \( m \) interferograms are formed, obviously \( m \geq n \) for the given network in Fig.1; \( A \) is a \( m \) by \( n \) matrix which represents the network structure and \( e \) is the observation noise vector.

One simple realization of Eq.(2), for example, can be: given a network formed with three acquisitions namely \( a, b \) and \( c \), \( y = (\phi^a_p, \phi^b_p, \phi^c_p)^T \), \( A = [1,-1,0; 0,1,-1; 1,0,-1] \) and \( x = (\phi^a, \phi^b, \phi^c)^T \), where \( T \) stands for the matrix transpose. Since the \( m \) interferograms are formed from the \( n \) acquisitions, so there are only \( n-1 \) independent interferograms and the other \( m-n+1 \) interferograms are the linear combinations of the \( n-1 \) independent interferograms. As a consequence, the matrix \( A \) in Eq.(3) has only \( n-1 \) linear independent columns. Thus, Eq.(3) is inherently ill-posed and it has an infinite number of solutions, even tough the number of observations in Eq.(3) is larger than or equal to the unknowns. To overcome the rank deficiency we need add one or more constrains to Eq.(3). One of the choices could be adding one or more external water vapor measurements (e.g. from GPS or MERIS in case of ASAR) acquired coincidently with the SAR acquisitions. However, these auxiliary measurements are not always available. Alternatively, we can take the temporal mean of APS as a constrain/pseudo-observation. Because of the weak correlation between spatial variations of water vapor at different acquisitions, the temporal mean will decay toward zero as the number of acquisitions increases. Hence, the constrained version of Eq.(3) can be written as:

\[
\begin{pmatrix}
y \\
y_0 = 0
\end{pmatrix} = 
\begin{pmatrix}
A & B
\end{pmatrix} 
\begin{pmatrix}
x \\
0
\end{pmatrix},
\]

where \( B \) is a \( 1 \times n \) vector with all its entries equal to \( 1/n \);

The weighted least squares (WLS) solution of \( x \) in Eq.(4) is given as [TST05]:

\[
\hat{x} = (A^T Q_x^{-1} A)^{-1} A^T Q_x^{-1} y,
\]

and the variance-covariance matrix (VCM) \( Q_y \) of the observation vector \( y \) reads:

\[
Q_y = 
\begin{pmatrix}
Q_y^x, & 0 \\
0, & Q_{y_0}
\end{pmatrix} = 
\begin{pmatrix}
A Q_x A^T + Q_e, & 0 \\
0, & 0
\end{pmatrix}^{-1},
\]

where \( Q_x \) is a \( n \) by \( n \) diagonal matrix which contains the variances of APS spatial variations during acquisitions; \( Q_e \) is the VCM of the phase noises and it is a diagonal matrix as well since we assume the phase noises in the interferograms are uncorrelated. To evaluate \( Q_e \) we use:

\[
\sigma^2_{\phi} = E[(\phi - \phi_0)^2] = \int_{-\pi}^{\pi} (\phi - \phi_0)^2 pdf(\phi)d\phi
\]

\[
= \int_{-\pi}^{\pi} \phi^2 pdf(\phi + \phi_0)d\phi,
\]
where \( \phi_0 \) is the expectation of \( \phi \). In our case, \( \phi_0 \) is corresponding to the mean phase delay in the resolution cell. Since the phase delay at short distances (e.g. < 1 km) can be considered as a constant, hence \( \sigma_{\phi}^2 \) is actually the variance of the phase noise. For distributed scatters with Gaussian or Rayleigh scattering, the phase pdf in Eq.(7) has the form [TBQ95]:

\[
pdf(\phi, \gamma, L, \phi_0) = \frac{1 - |\gamma|^2}{2\pi} \left\{ \frac{\Gamma(2L - 1)}{\Gamma(L)^2 2^{2\gamma_0 L}} \times \right. \\
\left. \frac{(2L - 1)\beta + \pi}{(1 - \beta^2)L} + \frac{1}{(1 - \beta^2)L} \right\} + \frac{1}{2(L - 1)} \times \\
\sum_{r=0}^{L-2} \frac{\Gamma(L - 1/2)}{\Gamma(L - 1/2 - r)} \frac{\Gamma(L - 1 - r) \Gamma(L - 1)}{(1 - \beta^2)r + 2} \\
\]

where \( \beta = |\gamma| \cos(\phi - \phi_0) \); \( L \) is the multilook factor; \( \gamma \) is the complex coherence. Note, Eqs.(7) and (8) show that we do not need to know \( \phi_0 \) in order to evaluate \( \sigma_{\phi}^2 \). The magnitude of the complex coherence \( |\gamma| \) can be estimated by [SC96]:

\[
|\gamma| = \frac{\sqrt{\sum_{n=1}^{N} y_1 y_2^*}}{\sqrt{\sum_{n=1}^{N} |y_1|^2 \sum_{n=1}^{N} |y_2|^2}}
\]

where \( y_1 \) and \( y_2 \) are the complex signals of master and slave respectively and * denotes the complex conjugate. In practice, the estimate \( |\gamma| \) is biased towards higher values, i.e. \( |\gamma| > |\gamma_{true}| \), for low coherence and/or small estimation windows [TBQ95]. Numerical evaluations of the phase pdf in Eq.(7) with varying \( |\gamma| \) and \( L \) are shown in Fig. 2a, b and c. The phase variance integrated numerically using Eqs.(7) and (8) as a function of \( |\gamma| \) and \( L \) is plotted in Fig. 2d. Note, for large \( L \) (i.e. \( L > 80 \)) the phase variance \( \sigma_{\phi}^2 \) turns to depending on the coherence magnitude \( |\gamma| \) only.

To realize \( Q_x \) in Eq.(6) we need know \( Q_x \) as well. To estimate \( Q_x \), however, we need know the parameter \( x \) which is unknown and needs to be estimated. Therefore, we have to compute \( x \) iteratively and in each iteration we compute \( Q_x \) based on the estimate of \( x \) from the previous iteration. The initial approximation of \( Q_x \) can be a null matrix with all zeros. After several iterations the update of \( Q_x \) becomes trivial and therefore the WLS of \( x \) can be obtained.

Finally, we need to stress that although APS at all acquisitions within the network in Fig.1 can be estimated uniquely using Eq.(5), their estimates have different accuracies depending on their locations in the network. Assuming same noise level for all interferograms in the network, the accuracy of the estimates at the network arcs (the dashed lines in Fig.1) which are not in the closed loop of the network (the solid lines in Fig.1) are lower than the accuracy of the estimates at the arcs within the loop. This is because there is no observation redundancy at the open arcs and therefore the noise in their observations cannot be adjusted. Moreover, for the same reason it is not possible to validate the estimates and remove possible outliers at these open arcs. Estimates validation and outliers detection are discussed in the following section.

2.2. Validation and detection

The estimates \( \hat{x} \) obtained from WLS might be biased with respect to its true but unknown value due to outliers in the observations (i.e. unwrapped interferometric phases). Many factors can cause outliers in the interferograms, e.g. phase unwrapping error, mis-coregistration between master and slave, DEM error which increases as the perpendicular baseline increases. Moveover, invalid estimates can also be caused by the error in the stochastic model, i.e. the VCM \( Q_x \) of the observations in Eq.(6). The error is likely to occur when the pixels used to estimate the coherence in Eq.(9) have low signal-to-noise ratio (SNR). In such case, the estimated phase noise variances from Eq.(7) for these pixels are under-estimated, i.e. \( \sigma_{\phi}^2 < \sigma_{\phi,tru}^2 \). Therefore, the need for testing the validity of the estimates is obvious. We propose a testing procedure which is commonly used to detect outliers in the geodetic networks. The procedure can be generally described by three steps: detection, identification and adaptation (DIA) [Teu00]. Firstly, in the detection step a null-hypothesis, which assumes the model described by Eq. (4) is well supported by the data (i.e. observations), is tested against general model mis-specifications. In some literatures this step is also called as overall model test (OMT) since it checks the overall validity of the model without the need to specify any particular alternative hypothesis. The appropriate test statistic for this step reads:
\[ T_{q=m-n}^{\text{crit}} = \hat{e}^T Q_{y}^{-1} \hat{e}, \]  

(10)

where \( \hat{e} \) is the WLS residue which is equal to \( y - Ax \); \( m, n \) are the number of observations and unknown parameters respectively, \( m-n \) is the observation redundancy. The null hypothesis is rejected when \( T_{q=m-n}^{\text{crit}} > \chi^2_{\alpha}(m-n, 0) \), where \( \chi^2_{\alpha}(m-n, 0) \) is a central Chi-square distribution with \( m-n \) degrees of freedom and \( \alpha \) is called the level of significance which represents the likelihood of a type-I error of the test. The type-I error is caused by postulating the reliable observations as outliers which are therefore rejected by the test. On the other hand, there is a type-II error (the likelihood is denoted as \( \beta \)) which is the result of accepting the outliers in the observations. Given the type-II error \( \beta \) the power of the test is \( \gamma = 1-\beta \). These two types of errors are always co-exist in all hypothesis based tests. Moreover, a decrease of \( \alpha \) will result in an increase of \( \beta \) and vice versa. Therefore, there is no hypothesis test which can minimize \( \alpha \) and \( \beta \) simultaneously.

To get out of the dilemma, in practice, it is common to fix one type of error and then try to minimize the other type. The test (among all tests) which gives the minimum \( \beta \) for a fixed \( \alpha \) is called a most powerful test since it maximizes the power of the test. In our case, we cannot afford rejecting correct observations since they are not re-measurable. Therefore a small \( \alpha \), e.g. 0.001 should be chosen. Assume maximally 10% of the interferometric phases within the closed loop of the network in Fig. 1 are outliers, \( \alpha \approx 0.001 \) implies that 1% of the identified outliers actually were correct observations. Obviously, the value of \( \alpha \) should be increased as the noise level of the observations increases. Next, if the null hypothesis in the first step is rejected then it implies that there most likely exists one or more significant model mis-specifications due to outliers. The task of the second step, i.e. identification, is therefore to detect the outliers in the observations. For simplicity, we assume there is only one outlier in the observations and the test statistic for detecting the outlier reads:

\[ w_i = \frac{e_i^T Q_{y}^{-1} \hat{e}}{\sqrt{e_i^T Q_{y}^{-1} Q_{y}^{-1} e_i}}, \]  

(11)

where \( Q_y = Q_y - A(A^T Q_y^{-1} A)^{-1} A^T \) is the VCM of the least squares residue \( e \); \( c_{ij} \) is a unit vector having the 1 as its ith entry. It can be shown that the \( w \) test in Eq.(11) is a most powerful test [Teu00]. The jth observation is suspected to be an outlier when \( |w_j| > |w_i| \) for all \( i \neq j \) and \( |w_j| > N_c(0,1) \), where \( N_c(0,1) \) denotes the standard normal distribution. In the last step, the detected outlier, i.e. the observation \( y_j \), is rejected and the parameters of interest are re-estimated using Eq.(5). The testing procedure iterates until there is no outlier can be identified with the given \( \alpha \). Note, as mentioned in the end of section 2.1, the outlier detection is not possible for acquisitions which are not included in the closed loop of the network. Therefore, either discard the APS estimates for these acquisitions or just accept them without reliability assessment.

2.3. Spatial filtering and interpolation

After testing, we obtain the pixel-wise APS estimates at all acquisitions. However, there can be pixels which do not have APS estimates at some acquisitions. This is because for these pixels Eq.(4) is ill-posed due to the rejection of outliers at these pixels after testing. On the other hand, there are pixels with APS estimates but the estimates are strongly contaminated by noise. The noise in these estimates is propagated from the outliers which are not detected by testing due to the inherent type-II error. This error is normally not negligible since during testing the type-II error \( \alpha \) is fixed to a small value to prevent rejecting correct observations. Therefore, the purpose of spatial filtering and interpolation described in this section is to refine the estimated APS and to interpolate APS at locations where no APS estimates are available. The filtering and interpolation are implemented by ordinary kriging which gives the unbiased estimation of the signal of interest, meanwhile its filtering/interpolation error is minimized in a least squares sense. To refine/interpolate APS at location \( h_0 \) from its surrounding APS estimates (tested), the kriging equation reads:

\[ X(h_0) = \sum_{i=1}^{N} \lambda_i X(h_i), \quad h \in R^2 \]  

(12)

where \( \lambda_i \) is the kriging weight for the sample \( X(h_i) \) at location \( h_i \). The kriging weights can be computed by solving the system of equations:

\[ \begin{pmatrix} \gamma(\Delta h_{12}) & \ldots & \gamma(\Delta h_{1N}) \\ \gamma(\Delta h_{21}) & \ldots & \gamma(\Delta h_{2N}) \\ \vdots & \ddots & \vdots \\ \gamma(\Delta h_{N1}) & \ldots & \gamma(\Delta h_{NN}) \end{pmatrix} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_N \end{pmatrix}, \]  

(13)

where \( \gamma(\Delta h_{ij}) \) is called semi-variogram; \( \mu \) is a Lagrange multiplier. To uniquely determine the kriging weights \( \lambda \), the left hand side \( N+1 \) by \( N+1 \) matrix in Eq.(13) needs to be positive-definite and therefore invertible. To meet the positive-definite requirement we first compute the raw semi-variogram by:

\[ \gamma(\Delta h_{ij}) = \frac{|X(h_i) - X(h_j)|^2}{2}, \]  

(14)

and then we fit the raw variogram to a Matérn family model which can describe the well-known ’2/3’ law of the Kolmogorov turbulence theory [Tat61]. Assuming that the estimated APS is wide-sense stationary (otherwise we pretend it), the model for the variogram can be obtained from:

\[ \gamma(\Delta h) = C(0) - C(\Delta h), \]  

(15)

where \( C(\Delta h) \) is the covariance function of the Matérn class. The function reads [Ste05]:

\[ C(\Delta h) = \frac{c}{2^{\nu-1} \Gamma(\nu)} (\alpha |\Delta h|)^\nu K_\nu(\alpha |\Delta h|), \]  

(16)
Figure 3. The area (green square) chosen for the case study is located in south-western Australia with scene centered at 30.36°S and 117°E. The red polygons outline the dried salt lakes. The local time of the acquisitions is 9:40 am.

Figure 4. Wrapped interferometric phases of the case study area with different temporal baselines; (a): 35 days; (b): 70 days; (c): 105 days; (d): 140 days; (e): 175 days; (f): 210 days; (g): 350 days; the coherent parts in (g) is corresponding to the dried lakes outlined in Fig.3

where \( c \) denotes the variance (power) of the turbulence; \( \alpha \) represents the correlation length of the turbulence; \( \nu \) defines the smoothness of the turbulence; \( \Gamma \) is the Gamma-function and \( K \) is the modified Bessel-function of the second kind.

3. CASE STUDY

3.1. Area of interest and data pre-processing

The area chosen for our case study is centered at 30.36°S and 117°E in south-west Australia, see Fig.3. The area is barely vegetated due to its regional semi-arid climate. As a result, the phase coherence can remain for a relatively long period (~ 6 months) as shown in Fig.4. The time span of the acquisitions used in this study is between May 2005 and April 2008. To apply our algorithm discussed in Section 2 we assume the land deformation in the area is negligible during the period. Starting with the SLC (single-looking-complex) data, 40 interferograms with average 85 days temporal baseline and 205 m perpendicular baseline are formed from 22 ASAR images, see baseline plot in Fig.5. The area has a smooth topography with an average height of 250 m and the maximum height difference is about 200 m. Therefore the vertical stratification effect of APS is negligible in this area.

The topographic phase in all interferograms is modeled and subtracted using 3-arc-second SRTM data. To reduce phase noise due to geometric decorrelation [GMGP+94] a range filtering is applied to all interferograms to cut off non-overlapping spectra of master and slave. After phase unwrapping, a coherence based spatial average (i.e.multilook) is applied to the unwrapped phases to reduce random phase noise. The operation can be written as:

\[
\bar{\phi} = \frac{1}{\sum_{i=1}^{m} \sum_{j=1}^{n} w_{i,j}} \sum_{i=1}^{m} \sum_{j=1}^{n} w_{i,j} \phi(i, j), \quad (17)
\]

where

\[
w_{i,j} = \begin{cases} 
1 & \text{if } |\gamma(i,j)| > |\gamma|_{\min} \\
0 & \text{otherwise}
\end{cases} \quad (18)
\]

and \(|\gamma|_{\min}\) is a pre-defined coherence threshold (e.g. 0.35). Since APS is spatially smooth thus a large window size (e.g. 250 by 50 in azimuth and range respectively) for averaging is admissible without invoking signal aliasing. In this study we multilook the unwrapped interferograms to 1 km in both azimuth and range. After the multilook a surface trend is estimated from each interferogram and then the modeled trend is subtracted from the interferogram to mitigate other phase contributions, i.e. orbit error, hydrostatic and ionospheric delays [Han01].
The detrended phase has a zero mean and is wide-sense stationary. In the end, the phase delay is converted to the range delay in zenith by multiplying with \(-\frac{\lambda}{4\pi} \cos \theta\), where \(\theta\) is the radar side looking angle (23° for Envisat) and \(\lambda\) is the radar wave length, the minus sign is due to a phase increase corresponding to a range decrease.

3.2. Result validation

We validate our APS estimates from four different aspects: estimation bias, stochastic behaviour of the APS estimates, temporal correlation between the APS estimates and cross validation using MERIS respectively. The first three aspects do not need external and independent sources so we regard them as internal validations. By such a definition, the last aspect is therefore referred as an external validation in which MERIS water vapor measurements acquired under cloud free condition are compared to the corresponding APS estimates.

3.2.1. Estimation bias

The estimated APS is biased due to the added constrain (see Eq.(4)) which is the temporal mean of the APS at different acquisitions. It can be shown that the bias is a constant for all APS estimates and it is equal to the temporal mean which has a zero expectation. Given the estimated APS it is possible to evaluate the RMS of the bias (in terms of delay). Using the variance propagation law we find:

\[
\sigma_{\text{bias}}^{\text{APS}} = \sqrt{\frac{\sum_{i=1}^{22} \sigma_i^2}{22}} = 0.76\text{mm}.
\] (19)

By contrast, the mean RMS of the APS estimates is 3.6 mm which is about 5 times larger than the bias RMS. The histogram of the RMS for all APS estimates (in total 22) is shown in Fig.6b. As we can see that 17 out of 22 APS estimates do not have a RMS larger than 4 mm. The low RMS might be due to the semi-arid climate in the region. The rightmost bar in the histogram is corresponding to an acquisition probably with precipitation, see discussion in section 3.2.2. For comparison, the histogram of the APS derived from 11 MERIS IWV measurements on the same dates with clear sky is shown in Fig.6c. It can be seen from Figs.6b and 6c, the derived APS from InSAR and MERIS show similar amount of spatial variations.

3.2.2. Stochastic behavior

The raw variograms and power spectral densities (PSD) of the APS estimates are shown in Figs.7a and b respectively. The PSD are computed using the periodogram approach. The average of the raw variograms is plotted as the bold red line in Fig.7a. At short distances (i.e. a few kilometers) the slope (approximately 5/3) of the averaged variogram is steeper than the slope (dominated at 2/3) at larger distances and the slope turns to flat at the distances beyond about 40 km. The flattening effect is the result of the surface trend removal which was carried out for the interferograms to remove surface trends in them. Note, the uppermost raw variogram which corresponds to the APS spatial variation on date 08-Nov-06 is excluded from the averaging since it obviously causes a large bias in the averaged variogram. The MERIS cloud masks for this date indicate the sky of the area was completely covered by clouds. There might be some precipitation during the acquisition but we do not have any meteorological data to verify it. The averaged PSD is shown as the bold red line in Fig.7b. Its slope is also scale-variant, at large wavenumbers (\(> 0.4\) cycle/km) the absolute slope (approximately 8/3) is higher than the absolute slope at smaller wavenumbers and the dominant slope is of \(-5/3\).

The observed slopes of the variogram and PSD are consistent with the theoretic slopes of the atmospheric turbulence [Tat61] [Han01].
Figure 7. Stochastic analysis of all 22 APS estimates for the 22 ASAR acquisitions used in the case study. Since the interferograms used for APS estimation were significantly subsampled, only wavelengths above 1 km are shown. Furthermore, wavelengths above 50 km are truncated since the signal power does not increase anymore beyond the wavelength. (a) Computed raw variograms (solid black) and their average (bold red) using a log-log scale, the background dot lines follow a 2/3 and a 5/3 slope for reference. (b) Computed one-dimensional power spectra (solid black) using periodogram and their average (bold red), the background dot lines follow a -5/3 and -8/3 slope for reference.

Figure 8. Correlations between the APS estimates for 22 ASAR acquisitions. The elements in the main diagonal are the auto-correlation of the APS estimates. The elements in the off diagonal represent the cross-correlation between the APS estimates for different dates.

3.2.3. Temporal correlation

It can be shown (see [Han01]) that the sum or difference of two APS from different acquisitions has the same power-law behavior described in Section 3.2.2. Therefore, the stochastic analysis cannot discover any mixture of APS from different acquisitions. A mixture of APS can result in a considerable correlation between the APS estimates. Hence, we compute the cross-correlation between the APS estimates of different dates to detect any possible mixture, see Fig. 8. Despite a few APS estimates show some considerable cross-correlation, the mean of the overall cross-correlation is as low as 0.1. Therefore, the mixture of APS from different acquisitions should be very limited.

3.2.4. Cross validation with MERIS

Figure 9 shows some representative comparisons between the estimated APS and the delay spatial variations derived from the MERIS cloud free IWV measurements. Although large spatial correspondence between them can be clearly seen from the figure, the quantitative comparison, shown in Fig. 6a, between the two indicates some substantial inconsistencies between them. We believe the inconsistencies might be due to the cloud masking errors of MERIS (see the red ellipses in Fig 9) as well as the camera-interface effect (indicated by the black arrows in Fig. 9) of the on-board cameras (in total 5) which scan the ground surface under a push broom mechanism [ESA06].

4. DISCUSSION AND CONCLUSION

In this paper we regard the observed APS in the interferograms as a source of signal which is closely related to the spatio-temporal variation of water vapor in the troposphere. Given a set of interferograms with small temporal and perpendicular baselines, we propose an approach to estimate APS spatial variations at epochs of SAR acquisitions. The estimated APS is biased due to the added constrain which is needed by least squares to obtain a unique solution. The RMS of the bias is inversely proportional to the number of acquisitions involved in the constrain. It has been shown that the RMS of the bias in our APS estimation is 0.76 mm. The stochastic analysis of our APS estimates based on variograms and PSD shows the estimates obey the power-law behavior predicted by the turbulence theory. Moreover, the low cross-correlation be-
between the APS estimates indicates that the estimates are nearly uncorrelated in time. Despite some inconsistences between our APS estimates and the corresponding MERIS measurements due to the cloud masking errors and camera-interface problems of MERIS, the estimated APS in general has a good spatial correspondence with the MERIS measurements. Therefore, based on the internal and external validations we come to the conclusion that it is feasible to retrieve APS at epochs of SAR acquisitions provided that: 1. the land deformation is negligible in the area of interest or the deformation signal can be modeled and subtracted from the interferograms; 2. the number of SAR images in the network is sufficiently large (e.g. \( \geq 20 \) for semi-arid regions) to reduce the bias in the APS estimates; 3. decorrelation noise, e.g. temporal and geometric decorrelation, does not obscure the APS signal.

Due to the baseline constrains of current satellite missions, e.g. 1100 m critical baseline and minimum 35-day temporal baseline for ERS2 and Envisat, our approach cannot be widely applied. However, the approach will be generally applicable after the launch of the ESA’s new generation Earth Observation satellites Sentinel-1A/B. When these two satellites become operational the repeat orbit of the satellites will be reduced to 6-day for all land masses and the critical baseline is expected to be much larger than 1100 m because of the larger range bandwidth of the on-board SAR system.

5. ACKNOWLEDGMENTS

SAR and MERIS data used in this study were kindly provided by the European Space Agency, ESA. This study was funded by the ESA METAWAVE (Mitigation of Electromagnetic Transmission errors induced by Atmospheric WAter Vapour Effects) project (contract nr. 21206/07/NL/HE).

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