Efficient Approach for Atmospheric Phase Screen Mitigation in Time Series of Terrestrial Radar Interferometry Data Applied to Measure Glacier Velocity

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Abstract—The accuracy of surface displacements measured by differential radar interferometry is significantly degraded by the atmospheric phase screen (APS). This article presents a practical and efficient approach for APS mitigation based on the coherent pixels technique (CPT) displacement velocity estimation algorithm. In the proposed approach, all motionless coherent pixels closest to the moving area are defined as seeds surrounding the moving area at the integration step of the CPT. This arrangement consequently minimizes the integration path and the APS effect in the final velocity result. It is designed for terrestrial radar interferometry (TRI) applications. A piecewise processing chain is further introduced as a continuous operational mode processing framework to derive arbitrary temporal displacement patterns in this work. Three-day datasets measured by Ku-band TRI over a mountainous region in the canton of Valais, Switzerland, were used for validation. Through this validation, a comparative study of five algorithms was carried out. This evaluation showed the efficiency of the proposed approach. The proposed approach does not require phase unwrapping, kriging interpolation, and spatio-temporal covariance inference for APS mitigation, which is appropriate for continuous TRI operation.

Index Terms—Atmospheric phase screen (APS), glacier, ground-based radar interferometry, radar interferometry, terrestrial radar interferometry.

I. INTRODUCTION

FLEXIBILITY of the terrestrial radars in terms of acquisition timing, mode, and observation geometry can be a major advantage for interferometric measurements on a local scale as compared to spaceborne and airborne synthetic aperture radar (SAR) observations [1], [2]. Displacement estimation with submillimeter accuracy can be achieved using a dense time series of terrestrial radar interferometry (TRI) observations [3]. A wide variety of applications have been reported since 1997 [4]. In most applications, the differential interferometric SAR technique is used to estimate the displacement time series of targets by analyzing a series of TRI images. Those can be roughly categorized into specific purposes: landslide monitoring/prediction [5]–[7], minefield monitoring [8], [9], artificial structure monitoring (building [10], dam [11], bridge [12], tower [13], cultural heritage [14], and monument [15]), and glacier/snow monitoring [16]–[21]. Glacier monitoring addressed in this study is one of the key applications giving essential information for studying its variation as a response to climate change [22] as well as the potential risk detection of the glacier failures for an early warning [16]. Because of the fast-moving and decorrelated characteristics of the glacier, the measurements have been performed in continuous operational mode with a short temporal baseline.

The zero spatial baseline configuration of TRI minimizes several decorrelation sources. Even in this case, artifacts caused by atmospheric refractivity changes between temporally spaced acquisitions known as the atmospheric phase screen (APS) are observed. The APS has been categorized into stratified APS and turbulent APS components [23]–[25] over the mountainous area. The former component is observed in scenarios with vertical stratification of a refractivity index correlated with topography [26], [27]. The latter component, however, is caused by turbulence mixing, exhibiting spatial correlation, described by Kolmogorov’s turbulence theory [28]. A detailed analysis can be found in [29].

In these settings, time series interferometric SAR (InSAR) techniques enable reliable land displacement estimation [30]. Many of them share the rationale of the persistent scatterer interferometry [31], [32] and the small baseline subset [33].

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Also, the coherent pixels technique (CPT) developed in [34], [35] allows for efficient displacement estimation without the need for spatial phase unwrapping of interferograms. These time series InSAR techniques have also been adapted to TRI processing [36]–[38].

In general, spatio-temporal spectral filtering is used to estimate the APS in these algorithms. In addition, when applied to spaceborne SAR, external auxiliary data such as numerical weather prediction or other remote sensing datasets have been employed [39], [40]. However, such external auxiliary data is not appropriate for TRI applications because of the large spatial scale and relatively lower resolution.

Accordingly, several APS compensation methods for the TRI dataset have been developed. The data-driven model-based statistical approach is a popular method because of its simplicity and does not rely on auxiliary data [41], [42]. Correction of the stratified APS over steep topographic regions for TRI applications was first addressed in [26] and termed a multiple regression model (MRM). Subsequently, the simple linear model of the refractivity index in MRM was modified to take into account heterogeneous refractivity index distribution in [16], [43], [44] by introducing a higher order model. Studies in [45], [46] employed a piecewise regression approach to include a different atmospheric condition along the slant range direction. However, those stratified APS compensation methods cannot fully compensate APS under turbulent atmospheric conditions. The APS caused by turbulent mixing (turbulent APS) and the residual error of stratified APS still substantially impacts the final velocity estimation.

Thanks to the spatial correlation of the turbulent APS [29], the geostatistical kriging approach gives a spatial prediction on displaced locations [16], [43], [47]. The prediction by kriging interpolation is performed using surrounding motionless pixels. As a result, the turbulent APS is possibly corrected by subtracting the predicted APS from the corresponding interferogram. Furthermore, the temporal correlation of the turbulent APS was considered in a recent publication [16]. In specific, temporal correlated nuisance terms are taken into account in the temporal inversion of velocity using generalized least squares (GLS). In this methodology, the covariance of the interferometric error term, which is a superposition of APS and decorrelation phase terms, is explicitly included in the GLS estimator [25]. Although the GLS estimation can give the best linear unbiased estimator, it requires a high computational cost in covariance inference, spatial kriging interpolation, and spatial phase unwrapping. However, such processing is not practically applied to the near-real-time continuous displacement measurement, which requires rapid processing of time series InSAR results.

The presented work proposes applying the CPT algorithm for efficient APS mitigation with an introduced seed-setting strategy as a case study applied to TRI glacier monitoring. We focus on the seed location arrangement at the integration step of the CPT and give a practical approach that selects the multiple seeds around the displaced area. The proposed approach does not have any steps requiring a high computational cost compared to the geostatistical approach. Furthermore, the presented work introduces a piecewise processing chain for the estimation of arbitrary temporal displacement patterns. The evaluation and validation of the presented approach are performed under a controlled simulated environment. Furthermore, the dataset collected by TRI through a glacier measurement campaign is employed to evaluate our method.

The article is organized as follows. Section II introduces the TRI measurement campaign over the glacier in 2015 and hardware specifications. Section III investigates the spatial behavior of the presented turbulent APS in the acquired dataset. Section IV elaborates on the processing chain introduced in this article. Section V demonstrates the proposed APS mitigation approach with the sensitivity analysis by the random field simulation. Section VI presents the velocity estimation results of the acquired TRI dataset estimated by five methods. Finally, some discussions and conclusions are given in Sections VII and Section VIII, respectively.

II. DATA: TRI TIME SERIES OF A GLACIER

The experimental data used in this work is a time series of TRI data of the Bisgletscher, a steep and fast-flowing glacier located on the eastern side of the Weisshorn and Bishorn mountains in the Valais Alps above the village of Randa, Switzerland. The TRI data was acquired using the Ku-band advanced polarimetric radar interferometer KAPRI [48], [49], a fully polarimetric version of the real-aperture Gamma Portable Radar Interferometer [50], from July to August in 2015. The reader is referred to [49] for details on the KAPRI system and [16] for a comprehensive description of the test site and the Bisgletscher TRI measurement campaign.

The Bisgletscher was observed at a 2.5-min time interval to minimize temporal decorrelation and temporal phase wrapping, whereas limited data storage prevented us from selecting an even shorter time interval. The observation was made at an elevation of 2940 m from the Domhütte mountain hut, located on the opposite side of the valley. A photograph taken during this campaign in Fig. 1(a) shows Bisgletscher in the background as well as the radome containing the KAPRI. Fig. 1(b) shows the radar mounted on a pillar inside the radome.

KAPRI is a real aperture radar system based on frequency-modulated continuous wave architecture. The specifications of this radar are shown in Table I (detailed information is available in [49], [50]). The most available ground-based SAR generates
its radar images by synthetic aperture processing by a linear scan of the radar assembly on a rail. In contrast, KAPRI generates the radar images by rotational scanning, lining up the range profile along the azimuth direction without any synthetic aperture processing. The 2-m-long slotted waveguide antennas of the KAPRI have a 0.385° azimuth beamwidth, achieving high azimuth resolution. Operating in the Ku-band frequency range from 17.1 to 17.3 GHz, the range resolution of 0.75 m in the normal distance is achieved. Some calibration steps are required, especially for the polarimetric images, as described in [49].

### III. STOCHASTIC BEHAVIOR OF APS

The atmospheric phase term in a single look complex (SLC) image is defined by the refractivity index \( N_{\text{ref}}(r_s, t) \), which is a spatio-temporal function of the temperature, the pressure, and the partial pressure of water vapor [41] at the slant range \( r_s \) and the time \( t \), as

\[
\phi_{\text{atm}}(t) = 10^{-\pi} \frac{4\pi f_c}{c} \int N_{\text{ref}}(r_s, t) \, dr_s,
\]

where \( f_c \) accounts for center frequency, and \( c \) is the speed of light. APS can be expressed by taking the difference of two atmospheric phase terms measured at different time \( t_i \) and \( t_{i+1} \) as

\[
\phi_{\text{APS}}(t_i, t_{i+1}) = \phi_{\text{atm}}(t_i) - \phi_{\text{atm}}(t_{i+1}).
\]

Based on the physical origin, the APS observed over a mountainous area is categorized into two types of atmospheric signal: \( \phi_{\text{APS,atm}} \) caused by vertical stratification of \( N_{\text{ref}} \) and \( \phi_{\text{APS,turb}} \) caused by turbulent mixing of heat and humidity within the atmospheric boundary layer (ABL) [51], [52]. The \( \phi_{\text{APS,atm}} \) component behaves as low spatial frequency and correlates with topography. The model-based approach addresses to estimate \( \phi_{\text{APS,atm}} \) by approximating the spatial distribution of \( N_{\text{ref}} \) (see Appendix A).

On the other hand, the \( \phi_{\text{APS,turb}} \) component is often stochastically described by variogram, also known as structure-function [51], which describes spatial correlation structure. The variogram is defined by the variance of increment assuming the second-order stationarity of the increment, i.e., the expectation and covariance of increment are assumed not to be dependent on the location [53],

\[
\gamma(h) = \text{var} [\phi_{\text{APS,turb}}(x + h) - \phi_{\text{APS,turb}}(x)],
\]

which is called theoretical variogram, measuring the dissimilarity according to separation \( h \). In practice, experimental variogram is first computed over the high-quality pixels, the so-called coherent pixels (CPs) (see Section IV for CPs detection), by

\[
\gamma(h_i) = \frac{1}{2N_h(h_i)} \sum_{i=1}^{N_h(h_i)} (\phi_{\text{APS,turb}}(x_i + h) - \phi_{\text{APS,turb}}(x_i))^2 (h \in h_i)
\]

where \( N_h \) is the number of pairs within the given discrete distance \( h_i \). For our data, we assume that the variogram of \( \phi_{\text{APS,turb}} \) depends only on the distance, i.e., assuming isotropy of the turbulence.

A parametric variogram model is then fit to the experimental variogram to obtain a continuous variogram. Among several variogram models, this article uses the exponential model for variogram estimation of \( \phi_{\text{APS,turb}} \), given as [53]

\[
\gamma_{\exp}(h) = \sigma^2 \left( 1 - \exp \left( -\frac{h}{a} \right) \right),
\]

where \( \sigma^2 \) is the variance of the process (also known as sill) defined by variogram value at the infinity lag distance, and \( a \) is a so-called range of variogram. When \( h = 3a \), the exponential model reaches 95% of the \( \sigma^2 \); hence, this distance is called correlation length \( h_{\text{corr}} \) in this study (also known as a practical range).

Fig. 2(a) shows an example of the mean experimental variogram derived from 22 interferograms observed within 1 h (11:03–12:03, 14th July) as well as a fitted exponential variogram. Note that the stratified APS correction demonstrated in Appendix A is applied to all interferograms to take into account only \( \phi_{\text{APS,turb}} \). The derived variogram reveals that selected interferograms have \( \sigma^2 = 6.91 \text{ mm}^2 \) and \( h_{\text{corr}} = 659 \text{ m} \).

The isotropic turbulence-induced delay has a scale-variant power-law behavior described by Kolmogorov turbulence theory [28], [29], shown as

\[
\gamma(h) = D^2 (|h|)^{\alpha},
\]

where \( D \) is the strength of the turbulence and is assumed to be constant over all distances, and exponent \( \alpha \) corresponds to the correlation dimension. According to the previous studies in satellite radar interferometry [29], a variogram with a smaller distance than ABL thickness (~2 km) follows the exponent \( \alpha = 5/3 \), namely 3-D turbulence. In comparison, larger distance than ABL thickness is defined as 2-D turbulence with exponent \( \alpha = 2/3 \).

Fig. 2(b) shows the mean experimental variogram of three-days interferograms (in total 1404) formed by consecutive SLCs with a 5/3 and 2/3 slope. Although the \( \sigma^2 \) and \( h_{\text{corr}} \) of experimental variogram temporarily vary even within a day due to different solar heating of ground surfaces, we compute three-days averaged variogram to evaluate the general characteristic of the stochastic spatial behavior of \( \phi_{\text{APS,turb}} \) over the study area. The computed variogram reveals that the spatial statistics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center frequency</td>
<td>17.2 GHz</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>200 MHz</td>
</tr>
<tr>
<td>Range resolution</td>
<td>0.75 m 3DB resolution</td>
</tr>
<tr>
<td>Azimuth beamwidth</td>
<td>0.385°</td>
</tr>
<tr>
<td>Polarization</td>
<td>HH, HV, VV</td>
</tr>
</tbody>
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**TABLE I**

**SYSTEM PARAMETERS OF THE KAPRI**
shows a variation of both $\sigma^2$ and $h_{\text{corr}}$ along the time. At a glance, $\sigma^2$ of daytime shows a higher value (more substantial turbulence) than night-time while $h_{\text{corr}}$ of daytime shows shorter than that of night-time. Hence, the interferograms acquired during the daytime are much disturbed by turbulence than at night-time, resulting in significant error in displacement estimation.

IV. METHODS: PIECEWISE PROCESSING CHAIN

The $i$th measured interferometric phase ($\phi_{\text{measure}}^i$) in the zero spatial baseline configuration can be expressed by a summation of displacement phase term, APS ($\phi_{\text{APS}}^i$), and noise term ($\phi_{\text{decorr}}^i$), as

$$\phi_{\text{measure}}^i(x) = \frac{4\pi}{\lambda} T_i v(x) + \phi_{\text{disp, res}}^i(x) + \phi_{\text{APS}}^i(x) + \phi_{\text{decorr}}^i(x) + 2\pi n,$$

(7)

where $T_i$ indicates the time interval between reference and secondary SLC images, $x$ is a spatial pixel position vector, $v$ accounts for line-of-sight (LOS) surface displacement velocity, and $\lambda$ is the wavelength of the operational center frequency. The $\phi_{\text{disp, res}}$ accounts for a residual phase component of displacement that appears in the case of non-constant velocity (nonlinear displacement).

In near-real-time continuous operational mode, the processing chain needs to permit us the timely update of displacement time series. To fulfill this requirement, we apply displacement velocity estimation to a subset of the dataset; its schematic description is illustrated in Fig. 4. In this processing chain, velocity retrieval is performed when $N$ SLC images are obtained, and the processing waits until the following $N$ images are available. When we assume a short period (relative to displacement speed) in each time window, $\phi_{\text{disp, res}}^i$ in (7) can be negligible.

A constant velocity value is estimated using a subset of images. Therefore, the processing chain gives the time series of arbitrary displacement patterns by linking all the velocity values, as demonstrated in Fig. 4. Thus, the presented piecewise estimation approach allows for nonlinear displacements occurring at a larger time scale (beyond the time window chosen for the piecewise estimation).

At the beginning of the processing chain, interferograms are formed by means of the selected $N$ SLC images with the shortest temporal baseline criterion, referred to as the daisy chain. The daisy chain aims to minimize temporal decorrelation and phase wrapping issues along with the temporal domain [54] over the rapidly moving glacier area. For example, with given images acquired at times A, B, and C, we may form interferograms $\phi_{AB}$ using A and B as well as $\phi_{BC}$ using B and C, respectively; thus, the number of interferograms $M$ equals $N - 1$ in the daisy chain.

Before the velocity estimation, a selection of CPs is required to mask noisy pixels. Over the natural distributed area, the temporal mean absolute interferometric coherence criterion lying with the interval $[0, 1]$ is often used [33]–[35], [55] for CPs detection and
is defined as

\[
\bar{\gamma} = \frac{1}{M} \sum_{i=1}^{M} \left| \frac{s_i s_i^*}{\sqrt{s_i s_i^*} \sqrt{s_{i+1} s_{i+1}^*}} \right|
\]

where \(s_i\) (reference image) and \(s_{i+1}\) (secondary image) are complex values corresponding to the same pixel forming an interferogram, and \(\langle \cdot \rangle\) indicates the ensemble averaging with the assumptions of both stationarity and the ergodicity realized by spatial averaging. The pixels with higher \(\bar{\gamma}\) are then selected as the CPs.

However, the glacier tongue generally shows temporal decorrelation due to the physical displacement and potentially due to temporal changes of the glacier surface properties (e.g., surface moisture change). To illustrate this phenomenon, the coherence variations with respect to the temporal baseline from 0 to 1 h over the glacier tongue are shown in Fig. 5. The red plot indicates the result at a pixel showing the fastest displacement, whereas the blue plot indicates the coherence variation averaged over the glacier tongue. The computed results reveal a rapid coherence drop within 1 h, especially at maximum velocity pixel. According to this fact, the existence of “coherent pixels” seems to be doubtful over the glacier tongue as such regions show strong temporal decorrelation. Nonetheless, we herein assume that the pixels with higher mean coherence than the determined threshold are CPs, in practice. The employed processing defines the interferometric coherence threshold as 0.8 and uses the 7 × 2 (range × cross-range) rectangular window for multilook operation.

The stratified APS compensation is carried out for all interferometric pairs using a polynomial atmospheric phase model with respect to slant range and topographic height. The coefficients of this function are determined using an ordinary least-squares (OLS) solution. The pixels corresponding to the glacier locations should be masked before estimation to avoid biased estimate of the stratified APS parameters. Further details of the stratified APS compensation employed in this study are described in Appendix A.

Finally, velocity estimation is performed by means of interferograms after the stratified APS correction.

V. METHODS: PROPOSED APPROACH

This section elaborates on the proposed approach based on the CPT algorithm. Section V-A presents the zero-baseline CPT...
algorithm applied to TRI [36], [38]. A demonstration of the APS effects on the CPT and the multiple-seed approach are described in Section V-B. Section V-C evaluates the presented approach under a simulated environment.

A. Zero-Baseline Coherent Pixels Technique (CPT)

The CPT, developed at the Remote Sensing Laboratory of the Universitat Politecnica de Catalunya (UPC) [34], [35], works with phase increments between spatially separated pixels instead of the absolute phase. In the following, the zero-baseline CPT applied to TRI in [36], [38] is presented in the introduced piecewise processing chain framework.

In practice, Delaunay triangulation relates selected CPs to generate a nonoverlapped spatial triangles network. The interferometric phase increment over an arc between two pixels \( x_a \) and \( x_b \) is given as

\[
\Delta \phi_{i,a,b} = \frac{4\pi}{\lambda} T_i (v(x_a) - v(x_b)) + (\phi_{\text{error}}^i (x_a) - \phi_{\text{error}}^i (x_b)) = \frac{4\pi}{\lambda} T_i \Delta v(x_a, x_b) + \Delta \phi_{\text{error}}^i(x_a, x_b),
\]

(9)

where \( \Delta \phi_{\text{error}}^i \) is a phase error term after the stratified APS compensation step. This phase error includes the residual APS, temporal decorrelation, and noise component. The residual APS is the term caused by turbulent mixing \( \phi_{\text{APS, turb}} \) and an inhomogeneous condition of the atmospheric refractivity.

Once the triangulation is performed over the CPs, velocity increments on all arcs of the network are ready to be estimated. Estimation of velocity increments is performed by minimization of the cost function \( \Gamma_{a,b} \) in the complex plane defined as [34], [35]

\[
\Gamma_{a,b} = 2 \left( 1 - \frac{1}{M} \sum_{i=1}^{M} \text{Re} \left\{ e^{-j(\Delta \phi_{a,b}^i - \frac{4\pi}{\lambda} T_i \Delta v_{a,b})} \right\} \right).
\]

(10)

Through this minimization, the optimal value of \( \Delta v_{a,b} \) is estimated in each arc. For computationally efficient and accurate searching rather than brute-force way, the conjugate gradient method (CGM) can be applied [56]. Since the minimization is executed in a complex plane, possible phase wrapping does not impact the model adjustment of phase increments. Therefore, the CPT does not require spatial phase unwrapping.

Once we estimate the velocity increments over the arcs, the phase quality on the arcs is evaluated by the model coherence lying the interval [0, 1] defined in each arc as

\[
\gamma_{\text{model}}^{a,b} = \frac{1}{M} \left| \sum_{i=1}^{M} e^{-j(\Delta \phi_{a,b}^i - \frac{4\pi}{\lambda} T_i \Delta v_{a,b})} \right|.
\]

(11)

In this phase increment estimation step, we may discard the longer arcs to avoid the highly deviated phase increment values [35]. Besides, the arcs with smaller model coherence than a predefined threshold \( \gamma_{\text{thres}}^{\text{model}} \) are rejected at this stage. In this article, the model coherence threshold \( \gamma_{\text{thres}}^{\text{model}} \) is set as 0.8.

Finally, the absolute velocity at the remaining CPs is obtained through an integration process. For this purpose, the CGM is employed to seek a path-independent global solution [35]. The temporal coherence computed on the arcs will be used in the integration process as the weights through the CGM to reduce the impact of low-quality arcs. The CGM solves the linear equations of the matrix form

\[
W A_{\text{arc}} v = W \Delta v,
\]

(12)

where \( W \) is a \([p \times p]\) \((p \text{ is the number of survived arcs})\) square diagonal matrix which contains the model coherence, \( A_{\text{arc}} \) is a \([q \times 1]\) \((q \text{ is the number of survived CPs})\) incidence matrix defining the relationships between CPs and arcs, \( v \) is a \([q \times 1]\) vector of unknown absolute velocity values, and \( \Delta v \) is a \([p \times 1]\) vector of velocity increments. \( A_{\text{arc}} \) consists of \(-1, 0, \text{ and } 1\) for each row with \(-1\) and \(1\) for corresponding CPs and 0 for the rest. However, the system in (12) is underdetermined because the matrix \( A_{\text{arc}} \) is singular. Therefore, the velocity of pixels with known displacements called seed is fixed in (12). For this purpose, all columns of \( A_{\text{arc}} \) associated with selected seeds are set to 0, and the known absolute velocity values (usually 0) are added or subtracted from \( \Delta v \) [57]. We typically select stable areas unaffected by displacement as the location of the seeds (in this case, the ones outside of the glacier area). The estimated absolute velocity values by the integration process with CGM on survived pixels are the outcomes of the CPT.

B. Multiple-Seed Selection Approach

An impact of the residual APS effect in the CPT is herein demonstrated. We focus on the seed location arrangement at the integration step of the CPT and propose an effective seed setting strategy to minimize the APS effect on final velocity estimation.

Fig. 6(a) describes an example of the 1-D network consisting of CPs and a seed. A blue shade indicates moving area while all the pixels outside of this area are assumed to be motionless pixels. Let us consider the velocity estimation of CP-3 in Fig. 6(a) at an integration step. The absolute velocity on
CP-3 can be obtained by
\[
\hat{v}_3 = v_1 + (\Delta \hat{v}_{arc1} + \Delta \hat{v}_{arc2}),
\]
where the weights are neglected for simplification of this example. The expression in (13) implies two error propagation effects of the residual APS.

The first effect is the APS propagated due to the integration of $\Delta \hat{v}_{arc1}$ and $\Delta \hat{v}_{arc2}$. Such a velocity increment $\Delta \hat{v}_{arc}$ may contain phase error terms, including residual APS in addition to displacement velocity increment; hence, we can write
\[
\Delta \hat{v}_{arc} = \Delta v_{disp} + \Delta v_{APS, res}. \tag{14}
\]

The error propagation effect can be minimized when both CP-1 and CP-3 share a similar atmospheric disturbance. This assumption is usually acceptable if both pixels are spatially close and show a similar temporal APS behavior, corresponding to high spatial correlation. To display this phenomenon using the real TRI dataset, we plot the estimated velocity increment values with respect to the relative distance between CPs in Fig. 7. Because we only use motionless pixels outside the glacier tongue, the velocity increment in Fig. 7 shows only the atmospheric noises. Fig. 7 reveals that the APS velocity increment increases as relative distance increases. According to this fact, the amount of APS error is related to the path distance. This is because the spatial correlation between CPs decreases as relative distance increases.

The second effect is the APS on $v_1$ caused by APS integration along a prior path between the seed and the CP-1 as well as the APS effect on the seed. A significant APS effect is expected in case of a longer integration path between the CP-1 and the seed. Nonetheless, CP-1 can be a seed pixel with the knowledge of the actual displacement velocity value at the CP-1 [$v_1 = 0$ for an example in Fig. 6(a)]. By doing so, a column of $A_{arc}$ associated with the CP-1 is set to 0, equivalent to $v_1 = 0$ in (13). In this way, the APS effect at $v_1$ can be avoided, and only the integration of $\Delta \hat{v}_{arc1}$ and $\Delta \hat{v}_{arc2}$ will impact on $\hat{v}_3$ estimate.

To sum up, motionless CPs closest to the estimation pixels better be selected as the seed pixel to minimize the APS effect at the integration step. A shorter integration path between a seed and pixels of interest is preferable for an APS mitigation.

Let us expand the 1-D example to the 2-D practical case shown in Fig. 6(b). According to the conclusion of the 1-D case, we introduce a multiple-seed arrangement to minimize the APS effects at the integration step. All motionless CPs closest to the moving area are defined as seeds surrounding the moving area, as illustrated in Fig. 6(b). Consequently, this multiple-seed strategy minimizes the physical distance between seeds and pixels of interest toward mitigating the residual APS effect in final absolute velocity results.

C. Evaluation and Sensitivity Analysis

An evaluation and a sensitivity analysis of the multiple-seed strategy are performed under a simulated environment. 2-D isotropic zero-mean Gaussian random fields are generated with corresponding covariance matrices given by variogram [58], [59] to simulate the turbulent APS effect. For this purpose, we use the software package “RandomFields” written in the R language [60]. The exponential model is employed with varying correlation length $h_{corr}$ and variance $\sigma^2$ for this simulation. We simulate the turbulent APS on 300 × 300 pixels where each pixel is assumed to be $10 \times 10$ mm$^2$. Fig. 8 shows examples of produced random fields with different correlation lengths (Fig. 8(a): $h_{corr} = 500$ and $\sigma^2 = 1$; Fig. 8(b): $h_{corr} = 1500$ and $\sigma^2 = 1$).

We produce 24 interferograms for an interferogram stack. The velocity estimation is performed over the area inside a white dotted open circle indicated in Fig. 8. Note that we randomly select 30000 pixels out of 90000 pixels as CPs in this test. To evaluate the estimated velocity error with respect to seed location and the number of seeds, three types of approaches are applied and compared: 1) CPT with multiple seeds surrounding the estimation area (CPT-M), 2) CPT with a single seed located far from the estimation area (CPT-SF), and 3) CPT with a single seed located close to the estimation area (CPT-SC). Seed locations of both CPT-SF and CPT-SC are indicated by a white filled circle and triangle symbols in Fig. 8(b), respectively. Furthermore, for the sensitivity analysis, we vary $\sigma^2$ from 0.1 to 8 mm$^2$ with an increment of 0.1 as well as $h_{corr}$ from 500 to 2000 m with an
Fig. 9. RMSE value of the retrieved velocity over the estimation area with respect to $\sigma^2$ and $h_{corr}$ for three approaches. (a) CPT-M. (b) CPT-SC. (c) CPT-SF. (d) 2-D slice at $h_{corr} = 1500$ m. (e) 2-D slice at $\sigma^2 = 2$ mm$^2$.

increment of 100. Those ranges of two parameters are almost equivalent to the statistics of our dataset revealed in Fig. 3.

Fig. 9 shows the root-mean-square-error (RMSE) of retrieved velocity over the estimation area (actual displacement velocity value is 0 mm/h). For the comparison in a different view, we display 2-D plots of Fig. 9(a)–(c) with fixed $h_{corr}$ or $\sigma^2$ in Fig. 9(d) and (e).

Comparing the CPT-SF and the CPT-SC, the CPT-SC yields lower RMSE than the CPT-SF. Also, the result shows a strong fluctuation of RMSE in the CPT-SF plot. According to the result, a better estimate with respect to atmospheric turbulence can be achieved by placing a seed as close as possible to the area of interest. Comparing the CPT-M and the CPT-SC, the CPT-M yields lower RMSE than the CPT-SC. This fact reveals that the multiple-seed setting can minimize overall RMSE on final velocity outcome because integration paths between the estimation pixels and seeds become shorter. Furthermore, general trends of the three approaches reveal that when the $\sigma^2$ becomes higher as well as $h_{corr}$ becomes shorter, RMSE approaches a higher value. The maximum RMSE value of CPT-M results in 10.8 mm/h when $\sigma^2 = 8$ and $h_{corr} = 500$ for this simulation.

VI. EXPERIMENTAL RESULTS

The performance of the proposed approach was tested with a TRI HH-polarization dataset described in Section II. The processing chain presented in Section IV was applied to the 3-day time series dataset from 08:00 CEST 13th July to 00:00 CEST 16th July obtained through the glacier observation campaign. Although the TRI acquired images with 2.5 min time intervals, some interferograms were formed with more than 5-min temporal separation because of missing or incorrectly processed images. We rejected such interferograms in this analysis.

The main purpose of this section is to provide the velocity estimation results of five approaches for relative comparison in terms of accuracy, robustness, and computational time that will be discussed in Section VII. In addition to CPT-SF, CPT-SC, and CPT-M, pixel-wise velocity inversion methods with geostatistical approaches are applied as the conventional methods that can mitigate the residual APS, applied in [16]. The terminology of the additional two methods and the explanations are described as follows. Appendix B elaborates on further details of both approaches.

1) OLS-Kriging

The OLS is applied to the absolute phase system in (21) for pixel-wise velocity inversion, as expressed in (22). Kriging spatial prediction is performed over the moving area, applying to all interferograms before OLS inversion. The predicted turbulent APS by kriging is subtracted from the corresponding interferogram to correct APS. Simple kriging in (26) is selected as one of the kriging methods. The kriging system uses the nearest 400 neighbor CPs outside of the glacier (CPs considered to have zero displacements within the timespan of interest) to any prediction pixels.

2) Generalized least squares

The GLS is applied to the absolute phase system in (21) for pixel-wise velocity inversion, as expressed in (23). The covariance of the interferometric error term, which is a superposition
of APS and decorrelation phase terms, is explicitly included in the GLS estimator. Simple kriging-based APS correction is applied to all interferograms before inversion, similar to the OLS-Kriging.

Because both the OLS-Kriging and the GLS implement a kriging-based correction, estimation results are expected to have less APS contribution than the one without kriging with a price of the computational time.

Note that the CPT does not apply the 2-D spatial phase unwrapping operation. On the other hand, the OLS-kriging and the GLS perform 2-D-phase unwrapping to make the system in (21) linear using minimum cost flow algorithm [61] by GAMMA software. This aspect is related to computational cost.

A Validation With the Synthetic Data

First, the performance of the five methods was evaluated using synthetic dataset with simulated displacement. Displacement with a maximum velocity of 15 mm/h is added beside glacier tongue. The spatial extent is expressed by a 2-D Gaussian function. S1 and S2 represent the locations of investigation pixels for synthetic dataset. P1 and P2 indicate the locations of investigation pixels for test on the glacier. The red-filled circles indicate the locations of seeds for the CPT-SF and the CPT-SC.

B Test on Glacier

The performances of the five methods were evaluated over the glacier tongue indicated by the red borderline in Fig. 10. Fig. 14 displays examples of the LOS velocity map for five methods. The residual APS effects remained in the CPT-SF and the CPT-SC results, where the negative velocity caused by APS can be seen in Fig. 14(a) and (b). As visually confirmed, such APS effects were successfully corrected in the CPT-M and geostatistical methods. Fig. 15 displays the velocity maps of five methods averaged over 64 velocity images. Because we applied an averaging operation along the temporal axis, the APS errors in final velocity results are minimized. Thus, all methods result in a similar spatial velocity pattern, but the averaging operation sacrifices time series variability. From those figures, we visually confirm that the top part of the glacier shows a higher velocity than the bottom part. This conclusion agrees with estimates of the Bisgletscher displacement speed obtained by the offset tracking method on radar amplitude images [62].

Fig. 16 shows the standard deviation (SD) of the estimated velocity maps for five methods to visualize the robustness of retrieval. In total, 64 velocity maps were used for the derivation of the SD. The CPT-SC reveals the lower SD around the seed than pixels far from the seed, which is a similar phenomenon shown in Fig. 11(b).

Furthermore, the velocity time series of two locations at P1 and P2 indicated in Fig. 10 are given in Fig. 17 for the in-depth visualization of estimated velocity temporal behavior.

VII. DISCUSSION

This section provides itemized discussions of the results presented in Section VI. The applicability of the CPT-M is discussed by comparing its performance with the other four methods. The comparison among the CPT-M, CPT-SF, and CPT-SC is described in Section VII-A. The comparison between the CPT-M and geostatistical approaches is given in Section VII-B.
Fig. 11. RMSE maps derived by 64 velocity results (from 13th July to 15th July) over the simulated displacement pixels. (a) CPT-SF. (b) CPT-SC. (c) CPT-M. (d) OLS-kriging. (e) GLS.

Fig. 12. Scatter plots of the true velocity versus the estimated velocity over the simulated displacement location. Corresponding RMSE and $R^2$ values are drawn at the top of each figure. Color represents the density of plots (the number of plots for each figure is restricted to 10 000 for the clear visualization purpose). (a) CPT-SF. (b) CPT-SC. (c) CPT-M. (d) OLS-kriging. (e) GLS.

Fig. 13. Time series plots of LOS-simulated displacement velocity at selected two pixels ($S_1$ and $S_2$). The constant velocity values are retrieved by a subset of images within 1 h. The top figures show the results of CPT-SF, CPT-SC, and CPT-M. The bottom figures show the results of CPT-M, OLS-kriging, and GLS. True velocity is plotted as red color. (a) $S_1$. (b) $S_2$.
A. Comparison With CPT-SF and CPT-SC

From the RMSE of the simulated displacement shown in Fig. 11, a noticeable improvement is seen in the CPT-M, compared to the two methods. Fig. 11 reveals significant impacts of residual APS effects on final velocity results in the CPT-SF and the CPT-SC cases. The scatter plot of the CPT-M in Fig. 12 shows the lowest RMSE and highest $R^2$. Diffuse scatter plots in the CPT-SF and the CPT-SC visually indicate the residual APS influences. Also, the CPT-M presents the velocity time series with less error than the other two methods in Fig. 13. Table II demonstrates that the CPT-M yields the lowest RMSE values at both S1 and S2.

The above consequences also appear in results over the glacier tongue. Fig. 16 shows that the CPT-M yields the lowest SD over the glacier tongue. Similarly, the CPT-M gives the velocity time series with less fluctuation than both CPT-SF and CPT-SC, as shown in Fig. 17. These results prove the robustness of the CPT-M against atmospheric disturbances.

The obtained results indicate that the multiple-seed-setting approach effectively mitigates the residual APS at the integration step. Consequently, the CPT-M yields higher accuracy than the single-seed arrangement without increasing the computational cost.

B. Comparison With Geostatistical Mitigation Approaches

A high computational burden in spatial kriging interpolation applied to all interferograms should be considered for the OLS-kriging and the GLS. In addition to kriging, the GLS requires the inference of covariances $\Sigma_{atm}$ and $\Sigma_{decorr}$ by all possible pairs of phase unwrapped interferograms for better estimation, requiring an additional computational cost. In contrast with the geostatistical methods, the CPT-M does not require such high computational processing. In a big O notation, the computational time of the CPT-M is $O(q)$, where $q$ is the number of velocity estimation pixels. On the other hand, the geostatistical approaches require $O(qn^3)$, where $n$ is the number of neighbor pixels (motionless CPs) used for weights determination and weighted average in (26) at kriging interpolation. Nonetheless, according to the results, the estimation accuracy of the CPT-M seems to be very similar to both the OLS-kriging and the GLS.

From Fig. 11, we recognize that the CPT-M shows the RMSE image almost equivalent to the other geostatistical methods over the simulated region. Accordingly, the scatter plots and corresponding RMSE and $R^2$ of the CPT-M in Fig. 12 are almost accordant with the others. This fact is confirmed in tabulated RMSE values in Table II for both S1 (center part)
Fig. 15. Mean LOS velocity results derived by TRI images from 08:00 13th to 00:00, 16th July. (a) CPT-SF. (b) CPT-SC. (c) CPT-M. (d) OLS-kriging. (e) GLS.

Fig. 16. SD of the estimated velocity derived by TRI images from 08:00 13th to 00:00, 16th July. (a) CPT-SF. (b) CPT-SC. (c) CPT-M. (d) OLS-kriging. (e) GLS.

and $S_2$ (outer part) points and corresponding time series results for three methods in Fig. 13.

The SD maps in Fig. 16 show similar results among the three methods over the glacier tongue. The same consequence is also given from the estimated velocity time series in Fig. 17(a) and (b), where the time series of the CPT-M is in agreement with geostatistical approaches.

When the contribution of the temporal covariance $\Sigma_{APS,t}$ in (25) is significant, the GLS inversion is advisable rather than the OLS-kriging as the solution gives us minimum variance and unbiased estimation. Nonetheless, the daisy chain adopted in our processing for interferogram pair selection makes diagonal variances of $\Sigma_{APS,t}$ constant (i.e., homoscedasticity) and does not show a high correlation among the
interferograms (i.e., off-diagonal covariances of the $\Sigma_{\text{APS},i}$ are expected to be close to zero) because selected interferograms according to the daisy chain do not share a reference image. Moreover, because the processing chain only uses the CPs for velocity retrieval, the covariance of decorrelation $\Sigma_{\text{decorr}}$ in (24) is expected to be close to zero. Due to such specific measurement conditions, the difference in performance between OLS-kriging and GLS appeared not significant in our analysis.

C. Advantageous Implications and Expected Applications of the Proposed Approach

Although the CPT-M proves to be an efficient estimation toward mitigating atmospheric disturbances, the exact knowledge of displacement location is required for the CPT-M as well as for geostatistical approaches. Nevertheless, the displacement location is often known in many applications. In the glacier measurement, a visual inspection may permit us the boundary detection of the moving part. Moreover, the data-driven moving area detection approach can be employed in a more robust manner. We observed that the glacier tongue showed a different scattering mechanism and a temporal scattering behavior from other regions over the cliff [63]. The temporal variation of the dielectric constant and the physical movement over the glacier tongue cause an amplitude variation and temporal decorrelation. Such characteristics lead to distinctive patterns of the glacier tongue from other regions. Therefore, several analyses, such as polarimetric target decomposition, DA, and interferometric absolute coherence, realize automatic glacier zone detection.

Finally, the CPT-M yielded almost identical accuracy to geostatistical methods with a lower computational cost. This advantage is especially significant in near-real-time monitoring. Recently, there is an increasing interest in multiple-input multiple-output (MIMO) radar for displacement monitoring [12], [64]. The MIMO radar allows fast acquisition of SAR images realized by the antenna array without physical movement of antennas; hence, it realizes real-time displacement monitoring.

The proposed APS mitigation approach is expected to be suited to such an operation, supporting the fast generation of accurate displacement time series.

VIII. CONCLUSION

The presented work proposes an efficient approach for APS mitigation in differential radar interferometry based on the CPT velocity estimation algorithm. The turbulent APS spatial behavior of our TRI dataset observed over the Bisgletscher is stochastically analyzed. The analysis reveals that the spatial statistic of the presented turbulent APS obeys a scale variant power low behavior. It also shows a temporal variation of the variance and the correlation length of the turbulence and reveals higher disturbance during the daytime than night-time.

A piecewise processing chain is introduced for the estimation of arbitrary temporal displacement patterns in this work. The introduced processing chain estimates the displacement velocity of each image subset, reconstructing arbitrary temporal displacement time series by linking all the results of subsets. A daisy chain is adopted in this processing chain to minimize temporal decorrelation and phase wrapping. The residual APS, which is the residual term after correction of the stratified APS, is further taken into account in the proposed approach.

A multiple-seed setting strategy is proposed as an add-on to the CPT algorithm toward mitigating residual APS. With a priori knowledge of displacement area, the proposed approach defines all CPs closest to the displacement pixels as seeds surrounding the moving area. An analysis by generated 2-D isotropic zero-mean Gaussian random fields reveals that the multiple-seed approach reduces the APS contribution on velocity estimation than single-seed cases. Moreover, the analysis shows that the variance and correlation length of the simulated turbulence limit the accuracy of the approach.

A case study of the glacier displacement measurement is carried out. The applicability of the proposed approach is tested.
with real TRI images acquired by KAPRI. The following consequences are obtained from the analysis through the comparison with different approaches.

1) The proposed approach reveals higher estimation accuracy and robustness than the CPT with a single seed. A multiple-seed setting effectively suppresses the residual APS accumulation effect at the integration step in the CPT.

2) The estimation accuracy of the proposed approach is almost as good as geostatistical approaches, i.e., the OLS-kriging and the GLS.

A noteworthy advantage of the proposed approach is its computational efficiency with a reasonable accuracy, which is considered as a proper APS mitigation for near-real-time operation.

APPENDIX

A. Stratified APS Compensation

According to (1) and (2), it is understood that modeling of \( N_{\text{ref}} \) will give the solution of \( \phi_{\text{APS,str}} \). Among the methods developed so far, we apply the model-based approach proposed in [43] in order to take into account the spatial heterogeneous \( N_{\text{ref}} \). The distribution of the \( N_{\text{ref}} \) is described by quadratic 2-D polynomial function with respect to a topographic height and a slant range. The unwrapped stratified APS model is then defined by means of relative slant range distance \( r_s \) and topographic height \( z_d \) from radar location to position of interest, given by

\[
\phi_{\text{APS,str}} (t_i, t_{i+1}) = \beta_0 + \beta_1 r_s + \beta_2 r_s z_d + \beta_3 r_s^2 z_d + \beta_4 r_s^2
\]

(15)

where \( \beta_0, \ldots, \beta_6 \) are the unknown parameters, and the \( \beta_0 \) shows the offset, \( x_1, \ldots, x_6 \) are observation variables. The matrix notation of (15) dealing with all the \( k \) candidates of pixels for estimation is given as

\[
\phi = X\beta + \varepsilon,
\]

(16)

where \( \phi \) is a \([k \times 1]\) vector of measured interferometric phase, \( \beta \) is a \([7 \times 1]\) dimension vector of the unknown parameters, \( X \) is a \([k \times 7]\) dimension vector of observation variables. The OLS inversion solves the unknown parameters \( \hat{\beta} \) as [26]

\[
\hat{\beta} = (X^T X)^{-1} X^T \phi.
\]

(17)

Finally, the estimated unknown parameters are substituted to (16) and the stratified APS can be estimated as

\[
\phi_{\text{APS,str}} = X\hat{\beta}.
\]

(18)

The observation variables in (17) should be chosen from the CPs unaffected by displacement contribution because the inclusion of moving pixels consequently leads to bias estimates. Therefore, we exclude the glacier parts from the selected CPs for unknown parameter estimation in (17).

It is important to highlight that the selected \( k \) CPs must be spatially unwrapped before the inversion to make the system in (16) linear. In practice, only sparse points out of all CPs can be used in the estimation because the stratified APS usually shows large-scale variation. By doing so, there is no need to perform the phase unwrapping for all CPs, and hence the computational cost is not regarded as significant.

B. Pixel-Wise Velocity Inversion

A signal model of the interferometric phase is expressed as a matrix form allowing all \( q \) candidate pixels as

\[
\phi = B \varphi + \varepsilon,
\]

(19)

where \( \phi = I_{q,1} \otimes \phi_x \) (\( \phi_x \) is \([M \times 1]\) vector of interferometric phases at pixel \( x \), and \( I_{q,1} \) is a \([q \times 1]\) identity matrix), \( \varphi = I_{q,1} \otimes v_x \) (\( v_x \) is the \([N \times 1]\) vector of velocities), \( \varepsilon \) is a noise-like component. \( B \) is the block diagonal matrix \([qM \times qN]\) computed by \( I_{q,q} \otimes B \), and \( B \) is an \([M \times N]\) matrix. In the dasy chain, \( B \) becomes

\[
B = \frac{4\pi}{\lambda} \begin{bmatrix}
T_1 & 0 & \cdots & 0 \\
0 & T_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & T_M
\end{bmatrix},
\]

(20)

where \( T_i \) indicates the time interval between reference and secondary SLC images (all must be 2.5 min in this study). Since the condition becomes \( M < N \) in this case, the rank of \( B \) becomes deficient, and no unique solution can be found for \( \varphi \) [16], [33]. By constraining the constant velocity assumption of \( v \) overtime as \( v = I_{N,1} \cdot p_x \) where \( p_x = v_0 (x) \), a system in (19) can be rewritten as

\[
\bar{\phi} = \bar{G} p + \varepsilon,
\]

(21)

where \( \bar{G} = \bar{B} \cdot (I_{q,q} \otimes I_{N,1}) \) , \( p \) is \([q \times 1]\) vector of constant velocity for all pixel candidates. The system in (21) now can be solved by OLS solution under linear system assumption as

\[
\hat{p}_{\text{OLS}} = (\bar{G}^T \bar{G})^{-1} \bar{G}^T \bar{\phi}.
\]

(22)

When the noise term in (21) is correlated both in time and space and/or indicating heteroscedasticity (varying variance), GLS estimation can give the best linear unbiased estimator as [65]

\[
\hat{p}_{\text{GLS}} = (\bar{G}^T \Sigma^{-1} \bar{G})^{-1} \bar{G}^T \Sigma^{-1} \bar{\phi},
\]

(23)

where \( \Sigma \) is the \([qM \times qM]\) covariance matrix of interferometric phase noise contributions, assumed to be the zero-mean Gaussian random process. Two noise terms of the residual APS and temporal decorrelation mainly degrade the signal quality. Thanks to the different physical mechanisms between APS and decorrelation, as well as linearity, the covariance matrix can be decomposed into residual APS \( \Sigma_{\text{APS}} \) and decorrelation term \( \Sigma_{\text{decorr}} \) as

\[
\Sigma = \Sigma_{\text{APS}} + \Sigma_{\text{decorr}}.
\]

(24)

An effective treatment under the assumption of separability is applied to \( \Sigma_{\text{APS}} \) for simplifying the statistic model in (24), where the separability implies that the spatial statistic is not a
function of time [16]. Under this assumption, the APS covariance \( \Sigma_{\text{APS}} \) can be further separated as a Kronecker product of spatial covariance \( \Sigma_{\text{atm}, s} \) and temporal covariance \( \Sigma_{\text{atm}, t} \) of SLC phases [16]

\[
\Sigma_{\text{APS}} = \Sigma_{\text{atm}, s} \otimes (A_{\text{inference}} \Sigma_{\text{atm}, t} A_{\text{inference}}^T) = \Sigma_{\text{atm}, s} \otimes \Sigma_{\text{APS}, t},
\]

(25)

where the \( A_{\text{inference}} \) is an \([M \times N]\) incidence matrix representing the interferometric combinations.

Although a large covariance matrix needs to be taken into account for the velocity inversion, a simple kriging (SK) interpolation can correct the spatial correlation of residual APS. Note that the method in [16] employed a regression kriging for the simultaneous estimation of the stratified APS and the residual APS. When the stratified APS has already been corrected, the SK can be applied assuming zero-mean over the field. Kriging interpolation predicts the residual APS by a weighted average of the local APS. In the kriging method, the weights are determined by the covariance of the spatial variables through the kriging system. The spatial prediction of unobserved residual APS by the SK at the arbitrary location \( x_0 \) of \( i \)th interferogram is given as [53]

\[
\phi_{\text{res,APS}}^i(x_0) = C_{0}^i T C_0^i \phi_{\text{neighbor, res}}^i,
\]

(26)

where \( C_0^i \) is an \([n \times 1]\) spatial APS covariance vector between \( x_0 \) and \( n \) neighbor CPs, \( C_0^i \) is an \([n \times n]\) covariance matrix of \( n \) neighbor CPs, and \( \phi_{\text{neighbor, res}}^i \) is the observed APS over the \( n \) neighbor CPs. The covariance values in (26) are inferred from the fitted exponential variogram model in this study according to experimental variogram measured over the motionless CPs [66] using the following relationship under the second-order stationarity:

\[
C(h) = \gamma_{\exp}(\infty) - \gamma(h),
\]

(27)

where \( \gamma_{\exp}(\infty) \) corresponds to the sill value (variance). Note that the relationship in (27) is only valid when the variogram is bounded by a finite value.

Finally, the predicted APS is subtracted from the interferogram to correct the spatial correlation. In this way, \( \Sigma_{\text{atm}, s} \) consequently becomes an identity matrix, resulting in the simplification of the covariance model in (25).

The remaining temporal covariance \( \Sigma_{\text{atm}, t} \) is inferred through the estimation of the temporal variogram model using all pairs of interferogram images \( N(N-1)/2 \). The exponential variogram model is also employed for the temporal covariance inference. Finally, decorrelation covariance \( \Sigma_{\text{decorr}} \) is obtained based on the exponential decay model of the temporal decorrelation (see step-by-step \( \Sigma_{\text{decorr}} \) estimation in [23]).

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