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A new approach to selecting coherent pixels for ground-based SAR deformation monitoring

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ABSTRACT

Ground-Based Synthetic Aperture Radar (GBSAR) is a flexible field-based remote sensing technology that, together with interferometric SAR (InSAR), has proven to be a powerful and effective tool for deformation monitoring. The Small Baseline Subset (SBAS) algorithm represents a typical advanced InSAR technique that extracts distributed scatterers from a network of interferograms for the measurement of time series displacement. However, it is well known that coherent points are variable from one interferogram to another, which renders time series analysis complicated. This study therefore proposes an effective approach to selecting coherent pixels from a network of interferograms, aiming to maximize the density of selected pixels and optimize the reliability of GBSAR time series analysis. A pixel is selected for the entire analysis if its coherent phase is capable of forming a full-rank coefficient matrix in the network inversion. A full-rank matrix means the pixel-dependent subset network is connected. Combining with the accurate estimation of coherence and interferometric phase based on sibling pixels identified from non-local windows, the proposed approach enables the selection of not only qualified partially coherent pixels but also persistent scatterers. The proposed approach has been incorporated into a bespoke GBSAR time series analysis chain for deformation monitoring, from which a mean velocity map, displacement time series and atmospheric phase delays can be determined. To validate the approach, experiments on two GBSAR datasets were performed. In both studies, sufficient coherent pixels were selected, suggesting the feasibility of the proposed coherent pixel selection algorithm. Displacement time series at the level of a few sub-millimeters were observed for both datasets, indicating the feasibility of the newly-developed GBSAR time series analysis chain for deformation monitoring, which is believed to lead to a wide range of scientific and practical applications.

1. Introduction

Hazards involving ground movements such as landslides, mudflows and the collapse of infrastructures are regular occurrences globally, often leading to significant human and economic losses. Such scenarios require effective monitoring of ground movements, which can give insight into mechanisms and triggering factors of hazardous events or act as the basis for mitigating risk, e.g. understanding maintenance and remedial measures, early warning and rapid decision-making for countermeasures or evacuation. Ground-Based Synthetic Aperture Radar (GBSAR) is a field-based imaging system offering users enhanced capabilities in monitoring surface displacements (Crosetto et al., 2017, 2015; Monserrat et al., 2014). More recently, GBSAR has proven to be a powerful remote sensing tool for deformation monitoring applications (Monserrat et al., 2014; Wujanz et al., 2013; Caduff et al., 2015). In comparison to spaceborne platforms, GBSAR has inherent advantages in terms of flexibility and portability which usually leads to a stack of consecutive acquisitions and offers opportunities for time series analysis. Interferometric Synthetic Aperture Radar (InSAR) time series analysis is the advanced form of the differential InSAR technique to identify and quantify ground movements based on multiple interferograms generated from a stack of SAR images (Ferretti et al., 2001; Lanari, 2007; Hooper et al., 2012).

Usually, a critical step in the processing of any InSAR time series analysis is the selection of coherent pixels with high Signal-to-Noise Ratio (SNR) in interferometric phase (Blanco-Sanchez et al., 2008). Further analysis and interpretation is then conducted only on the selected pixels. Amplitude Dispersion Index (ADI) and coherence are two commonly used criteria (Iglesias et al., 2014) for the selection of coherent pixels as they are strongly correlated with the standard deviation of the interferometric phase noise (Ferretti et al., 2001; Bamler and Hartl, 1998). According to the selection strategy and the processing of

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selected pixels, a number of InSAR time series analysis algorithms have been developed in the last two decades (Osmanoğlu et al., 2016). These algorithms fall into two broad categories: (a) Persistent Scatterer (PS) InSAR (Ferretti et al., 2001) which targets pixels with consistent scattering properties in time and viewing geometry, making this technique more suitable for artificial surfaces with sufficient back scatterers; (b) the more general Small Baseline Subset (SBAS) algorithm which uses distributed scatterers and singular value decomposition to connect independent unwrapped interferograms in time (Berardino et al., 2002; Lanari et al., 2004).

PS techniques are commonly based on a single-master configuration, with the main drawback of such techniques being the low spatial density of targets that behave coherently over the whole observation span (Perissin and Wang, 2012). By contrast, SBAS approaches construct a network of interferograms with multiple master images and small baselines (Shanker et al., 2011). However, as pointed out in (Spaans and Hooper, 2016), coherent points are variable from one interferogram to another, rendering time series analysis complicated. In other words, there are some partially coherent pixels (PCPs) that are coherent in some interferograms but not in others. Regarding the selection of coherent pixels in a redundant network, Crosetto et al. (2008) selected only pixels for which coherence was greater than a given threshold for all interferograms. PCPs were discarded in this approach, meaning the loss of some useful observations. Perissin and Wang (2012) formed a pixel-dependent network for each pixel by imposing a threshold on the coherence and only pixels with a connected network were analyzed. The subset of interferograms with respect to the minimum spanning tree graph in the network were used for the estimation of height and deformation trends. Such an approach fails to make the most effective use of redundancies and thus degrades the accuracy since a higher redundancy implies a more reliable displacement rate estimation. Therefore, a new selection criterion of PCPs is proposed in this paper that aims to maximize the density of selected pixels and optimize the reliability of GBSAR time series analysis by making the most of coherent phase redundancies.

Specifically, the method proposed in this paper forms a redundant interferogram network with a specified baseline threshold. A pixel-dependent matrix is then constructed for each pixel based on its coherence occurrences over all interferograms in the network. Pixels with a full-rank matrix are selected for further time series analysis. The proposed criterion enables the selection of not only qualified PCPs, but also persistent scatterers that behave coherently over all interferograms. Interferometric phase observations of selected pixels are spatially filtered and unwrapped. The inversion of the deformation trend is achieved only based on the coherent interferometric phase after filtering and unwrapping, which guarantees a reliable solution. In principle, the proposed approach supports any co-registered SAR datasets, but this paper only focuses on GBSAR deformation monitoring. The methodology is described in Section 2. The feasibility of the proposed method is verified by experimentation with two real-world GBSAR datasets in Section 3. The proposed approach is compared with the selection of coherent pixels using a single-pair GBSAR images and PS selection based on ADI in Section 4, where the justification of related parameters adopted in the proposed method are also discussed. Conclusions are drawn in Section 5.

2. Methodology

2.1. Selection criterion of coherent pixels

The phase difference at a point between two SAR images is called interferometric phase (Prati et al., 2010), which is the superposition of many terms including the topographic component, change resulted from surface movement in the light-of-sight (LOS) direction, variation of atmospheric delays, ambiguous cycles and noise. Analysis starts with a stack of SAR single-look-complex (SLC) images $(E_0, E_1, \cdots, E_N)$ relative to the same illuminated region, acquired at timest$(t_0, t_1, \cdots, t_N)$ in the chronological order. A redundant network of L interferograms formed by SLC images is assumed. The differential interferometric phase for a target between the SAR acquisitions at times t_M (for the master image) and t_S (for the slave image), can be written as:

$$\varphi^{w}_{t_M t_S} = \varphi^{Topo}_{t_M t_S} + \varphi^{disp}_{t_M t_S} + \varphi^{atm}_{t_M t_S} + \varphi^{noise}_{t_M t_S} - 2n\pi \tag{1}$$

where the superscript symbol w of the interferometric phase $\varphi^{w}_{t_M t_S}$ denotes that the value is wrapped into the range $[-\pi, \pi]$. The interferometric phase is actually a relative value due to the integer ambiguity n (Osmanoğlu et al., 2016). To obtain the absolute value, the recovery of ambiguity is required through a process known as phase unwrapping (Zebker and Lu, 1998). Thereafter, the unwrapped phase can be written as:

$$\varphi_{t_M t_S} = \varphi^{Topo}_{t_M t_S} + \varphi^{disp}_{t_M t_S} + \varphi^{atm}_{t_M t_S} + \varphi^{noise}_{t_M t_S} \tag{2}$$

where the topographic term $\varphi^{Topo}_{t_M t_S}$ is a function of the perpendicular spatial baseline (Prati et al., 2010). Unlike spaceborne SAR, GBSAR data can be acquired both continuously and discontinuously (Takahashi et al., 2013). Continuous operation offers a zero-baseline geometry, thus the topographic phase component is always zero. In a discontinuous campaign, topographic contributions arising from small repositioning errors can be corrected by treating it as a spatially smooth signal (Monserrat et al., 2014; Crosetto et al., 2014). Otherwise, the topographic term can be removed through the provision of a digital terrain model of the monitoring area and the precise geometry configuration of the radar equipment in the event of a significant spatial baseline. Without loss of generality, there are always at least three other terms that play a role in GBSAR interferometry (Crosetto et al., 2015):

$$\varphi_{t_M t_S} = \varphi^{disp}_{t_M t_S} + \varphi^{atm}_{t_M t_S} + \varphi^{noise}_{t_M t_S} \tag{3}$$

The goal of InSAR time series analysis for deformation monitoring is to obtain the deformation time series, denoted as $d^{disp}_{t_i} (i = 1, \cdots, N)$ with respect to a reference acquisition t_0. As recognised in previous studies (Berardino et al., 2002; Li et al., 2009), the mean velocity between time-adjacent acquisitions is a preferable choice in InSAR time series analysis in order to avoid large discontinuities in cumulative deformations and to obtain a physically reliable solution. In this case, no prior knowledge about the deformation is required in the network inversion. The displacement term in the interferometric phase can be expressed as:

$$\varphi^{disp}_{t_M t_S} = \frac{4\pi}{\lambda}[d^{disp}_{t_M} - d^{disp}_{t_S}] = \frac{4\pi}{\lambda}\sum_{k=M}^{S-1} v^{disp}_{k}\Delta t_k = \sum_{k=M}^{S-1}\varphi^{disp}_{t_k t_{k+1}}, \tag{4}$$

where v^{disp}_{k} is the displacement velocity and $\varphi^{disp}_{t_k t_{k+1}}$ is the associated phase change between the k^{th} and the $(k+1)^{th}$ acquisitions and t_k is the time interval between them. Similarly, the time-series atmospheric variation is denoted as $d^{atm}_{t_i} (i = 1, \cdots, N)$ and the atmospheric phase contribution in the interferometric phase can be written as:

$$\varphi^{atm}_{t_M t_S} = \frac{4\pi}{\lambda}[d^{atm}_{t_M} - d^{atm}_{t_S}] = \sum_{k=M}^{S-1}\varphi^{atm}_{t_k t_{k+1}} \tag{5}$$

where $\varphi^{atm}_{t_k t_{k+1}}$ represents the atmospheric phase variation between the k^{th} and the $(k+1)^{th}$ acquisitions. Together with Eqs. (4) and (5), the matrix form with respect to Eq. (3) can be generalized for the entire interferogram network:

$$\begin{cases} \mathbf{B}_{L\times N}\Phi_{N\times 1} = \delta\Phi_{L\times 1} + \varepsilon_{L\times 1}, \\ \Phi = [(\varphi^{disp}_{t_0 t_1} + \varphi^{atm}_{t_0 t_1})(\varphi^{disp}_{t_1 t_2} + \varphi^{atm}_{t_1 t_2})\cdots(\varphi^{disp}_{t_{N-1} t_N} + \varphi^{atm}_{t_{N-1} t_N})]^{\mathrm{T}}, \\ \delta\Phi = [\varphi_{t_1 t_2}\cdots\varphi_{t_M t_S}\cdots\varphi_{t_{N-1} t_N}]^{\mathrm{T}}, \end{cases} \tag{6}$$

where $\mathbf{B}$ is the coefficient matrix; $\mathbf{\Phi}$ is the matrix containing the incremental time series of phase change with respect to the superposition of both displacement and atmospheric variation; $\mathbf{\delta\Phi}$ is the matrix of