A New Non-local Method for Ground-based SAR Deformation Monitoring

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Abstract—Ground-based synthetic aperture radar (GBSAR) interferometry offers an effective solution for the monitoring of surface displacements with high precision. However, coherence estimation and phase filtering in GBSAR interferometry is often based on a rectangular window, resulting in estimation biases and resolution loss. To address these issues, conventional non-local methods developed for spaceborne SAR are investigated with GBSAR data for the first time. Based on investigation and analysis, an efficient similarity measure is proposed to identify pixels with similar amplitude behaviours and a comprehensive non-local method is presented on the basis of this concept with the aim of overcoming current limitations. Pixels with high similarity are identified from a large search window for each point based on a stack of GBSAR single look complex images. Coherence is calculated based on the selected sibling pixels and then enhanced by the second kind statistic estimator. Non-local means filtering is also performed based on the sibling pixels to reduce interferometric phase noise. Experiments were conducted using short- and long-term GBSAR interferograms. Qualitative and quantitative analysis of the proposed non-local method and other existing techniques demonstrates that the new approach has advantages in terms of coherence estimation and phase filtering capability. The proposed method was integrated into a complete GBSAR small baseline subset algorithm and a time series analysis was achieved for two stacks of datasets. Considered alongside experimental results, this successful application demonstrates the feasibility of the proposed non-local method to facilitate the adoption of GBSAR for deformation monitoring applications.

Index Terms—Ground-based synthetic aperture radar (GBSAR), deformation monitoring, interferometry, non-local, coherence estimation, filtering, time series analysis

I. INTRODUCTION

Ground-based synthetic aperture radar (GBSAR) is a field-based radar imaging system offering enhanced capabilities in mapping topography and monitoring ground displacements [1, 2]. GBSAR was originally adapted from spaceborne radar in the late 1990s [3, 4]. Similar to other radar systems, GBSAR has two types of observable: amplitude and phase [5]. The former is the strength of the back-scattered electromagnetic wave, which provides information on the reflectivity of the illuminated field [6]. The latter is related to the two-way distance that the measuring wave travels from the radar instrument to the target and then back to the sensor. A pair of amplitude and phase can be represented as a complex value and recorded in a SAR image. In comparison with spaceborne SAR, GBSAR has inherent advantages in terms of movability and fast

data collection [1, 2]. GBSAR (e.g. FastGBSAR manufactured by Metasensing [6]) can acquire SAR imagery with a temporal resolution of 5-10 seconds, and can be performed in continuous or campaign mode for different scenarios [1, 2, 7]. No matter which acquisition mode is adopted in a monitoring task, interferometry is the preferable and fundamental data processing technique for deformation monitoring applications [2], which are the focus of this study.

In processing, an interferogram can be formed by interfering two complex images, i.e. the pointwise multiplication between the master complex image and the conjugate of the slave image [8]. The phase difference between the master and slave SAR images is termed interferometric phase [9]. It is known that the interferometric phase suffers from both temporal and spatial decorrelations [10] which may lead to errors in phase measurements. Such noise can cause problems in phase unwrapping and hamper data interpretation [8]. Therefore, the interferometric phase quality should be guaranteed for any applications of the technique. Efforts to address this have been made via two different strategies: coherence estimation and phase filtering. The coherence between two complex signals is strongly correlated with the standard deviation of the phase noise [11]. Thus, coherence is an efficient and commonly used indicator for masking out low-quality pixels in a SAR interferogram. The alternative strategy has been to increase the signal-to-noise ratio (SNR) of interferograms by means of filtering techniques [12-14]. Increasing the SNR leads to better phase statistics and less problems at the stage of phase unwrapping [8].

The coherence of a pixel is often estimated based on a rectangular window around it and phase filtering is implemented using local spatial averaging (multilooking) [15]. As reported in [13, 16], the adoption of local windows could result in biased estimates and resolution losses due to local heterogeneity. To address these issues, a prevailing approach is to select homogeneous or resembling pixels from the wider surroundings of each resolution cell for the estimation [13, 15-21]. Although, these methods are known by different names, here they are collectively termed “non-local” methods. Non-local methods are primarily distinguished by the selection strategy of homogeneous or resembling pixels and the majority have been specially designed only for either coherence estimation or phase filtering. Some representative works are briefly introduced in this section.

Deledalle, et al. [13] proposed a patch-based method (termed “nl-InSAR”), in which the patch similarity was measured by the conditional probability of the intensity and the interferometric phase. Coherence, reflectivity and interferometric phase were jointly obtained by estimation of the covariance matrix. The process involved an iterative weighted maximum likelihood estimation with weights iteratively refined based on similarity. This technique used only an interferometric pair of co-registered SAR images. The iterative process, however, was not computationally efficient [13, 22].

Ferretti, et al. [19], on the other hand, exploited the statistics of time-series amplitude of two pixels within a window and constructed a probability distribution on basis of the statistics. Statistically homogeneous pixels (SHPs) were detected using a nonparametric hypothesis test, namely the Kolmogorov–Smirnov test [23]. The method required at least twenty SAR acquisitions to effectively reject the null hypothesis and obtain reliable results [21]. This technique has been integrated into the “SqueeSAR” software. Jiang, et al. [21] improved the selection of SHPs by forming a different probability distribution (Chebyshev’s inequality) which increased the interval estimate of the hypothesis test based on the central limit theorem (CLT). By taking this measure, the required number of acquisitions could be reduced. This method is termed “FaSHPS” due to its high computational efficiency. In addition, Goel and Adam [15] utilised the Anderson-Darling test to identify SHPs which were then used for coherence estimation and adaptive multilooking. This non-local method was combined with the small baseline subset (SBAS) algorithm for high resolution deformation monitoring in non-urban areas.

Spaans and Hooper [16] named resembling pixels “siblings”, with siblings extracted simply by utilising two statistics: mean amplitude over all interferometric combinations, and mean amplitude difference between master and slave images over all interferometric combinations. The simple computation ensured that the identification of siblings was a fast process and the method was thus termed “RapidSAR”. Contrary to statistical hypothesis testing techniques, which tend to result in a binary outcome, this method could easily maintain a minimum number of pixels with similar statistics for robust calculation in cases of insufficient siblings.

The aforementioned non-local methods were originally developed for the purposes of processing spaceborne SAR imagery. This study is thus dedicated to developing a versatile non-local method which addresses the three critical issues in GBSAR interferometry for deformation monitoring and possesses advantages over conventional non-local methods originally developed for spaceborne SAR: (a) the efficient and reliable identification of sibling pixels; (b) the accurate coherence estimation and phase filtering; and (c) the application of the developed non-local method in GBSAR time series analysis. To this end, several hypothesis tests and statistics, typically employed in representative works, are first investigated with actual GBSAR data. Based on investigation and analysis, a new similarity measure is developed to

overcome current limitations. The similarity is based on the mean of time series amplitude. Pixels with high similarity are selected from a non-local window for each point. Coherence is calculated based on the selected sibling pixels and then enhanced by a second statistical estimator [24, 25]. Non-local means filtering is also performed using the extracted siblings to reduce interferometric phase noise.

The developed methodology is described in Section II. The feasibility of the developed non-local method is verified by experiments with actual GBSAR datasets in Section III. In particular, the performance of the proposed method on the estimation of coherence and phase is evaluated and compared with other techniques, including the “boxcar”, “nl-InSAR” and “FaSHPS” estimators. Moreover, the proposed non-local method is integrated within a complete GBSAR SBAS algorithm. The results of GBSAR time series analysis are also presented in Section III. The justifications of parameters involved in the proposed method are discussed in Section IV. Conclusions are addressed in Section V.

II. METHODOLOGY

A. Identification of Siblings

The identification of sibling pixels is the basis of any non-local method. To investigate the feasibility of several non-local methods to GBSAR imagery, twelve pixels were manually selected from four different types of ground target using a stack of 60 GBSAR single-look-complex (SLC) images of the dataset depicted in section III for the identification analysis. The time series of amplitude values for the selected pixels are shown in Figure 1. Pixels with the prefix “A-” were selected from castle roofs which is made of stone. The properties of “B-” and “C-” pixels are not clear, but based on knowledge of the illuminated region most likely correspond to weathered rocks and earth / vegetation. Pixels of prefix “D-” were selected from the background area without backscatter.

Statistics (i.e. mean amplitude and mean amplitude difference over all interferometric combinations) used in [16] were firstly computed by considering the first SLC as the single master in the interferogram network and all the successive images as slaves. The percentage values of the two statistics for all pixel pairs are summarized in Tables I and II, respectively.

Unfortunately, the two measures were not able to identify resembling pixels, no matter what threshold values were chosen. Firstly, both of the two percentage measures depend on the statistics owned by the current pixel as denominators. Therefore, they cannot provide symmetric results and the results may fluctuate dramatically when denominators are close to zero, which can be witnessed by pixels of class “D”. Secondly, the amplitude time series of some samples, such as pixels “A-2”, “A-3” and all “D-”, remain relatively stable over all acquisitions. For these pixels, the mean amplitude difference between the master and slaves can be close to zero. Thus, the percentage of the mean amplitude difference for these pixels also varies dramatically and cannot be used as a valid estimator.

TABLE I
PERCENTAGE OF THE MEAN AMPLITUDE FOR ALL PIXEL PAIRS

	A-1	A-2	A-3	B-1	B-2	B-3	C-1	C-2	C-3	D-1	D-2	D-3
A-1	0.00	0.19	0.25	0.64	0.65	0.72	0.90	0.93	0.83	1.00	1.00	1.00
A-2	0.23	0.00	0.08	0.56	0.57	0.66	0.88	0.91	0.79	1.00	1.00	1.00
A-3	0.34	0.09	0.00	0.51	0.53	0.63	0.87	0.90	0.77	1.00	1.00	1.00
B-1	1.76	1.25	1.06	0.00	0.04	0.24	0.73	0.79	0.52	1.00	1.00	1.00
B-2	1.86	1.33	1.13	0.04	0.00	0.21	0.72	0.79	0.50	1.00	1.00	1.00
B-3	2.63	1.96	1.71	0.32	0.27	0.00	0.65	0.73	0.37	1.00	1.00	1.00
C-1	9.28	7.37	6.67	2.72	2.59	1.83	0.00	0.24	0.79	1.00	1.00	1.00
C-2	12.47	9.97	9.04	3.88	3.70	2.71	0.31	0.00	1.34	0.99	1.00	1.00
C-3	4.74	3.68	3.28	1.08	1.01	0.58	0.44	0.57	0.00	1.00	1.00	1.00
D-1	2285.8	1861.7	1704.3	827.3	797.9	628.53	221.4	168.82	397.14	0.00	0.88	0.73
D-2	18553.0	15112.3	13835.4	6719.9	6481.3	5106.8	1803.7	1376.9	3229.4	7.11	0.00	1.19
D-3	8487.7	6913.5	6329.3	3073.9	2964.7	2335.9	824.7	629.4	1476.9	2.71	0.54	0.00

Current pixels are arranged in row order while sibling candidates are in column order. A value < 0.15 (suggested threshold in [16]) is marked in blue, which indicates the resemblance of the corresponding pixel pair.

TABLE II
PERCENTAGE OF THE MEAN AMPLITUDE DIFFERENCE FOR ALL PIXEL PAIRS

	A-1	A-2	A-3	B-1	B-2	B-3	C-1	C-2	C-3	D-1	D-2	D-3
A-1	0.00	1.31	1.51	2.86	3.09	1.37	0.82	0.27	5.02	1.15	0.82	0.89
A-2	4.21	0.00	0.62	4.96	5.70	0.18	1.57	5.09	11.89	0.51	1.58	1.34
A-3	2.97	0.38	0.00	2.66	3.12	0.27	1.35	3.51	6.93	0.70	1.36	1.21
B-1	1.54	0.83	0.73	0.00	0.12	0.80	1.10	1.69	1.16	0.92	1.10	1.06
B-2	1.48	0.85	0.76	0.11	0.00	0.82	1.09	1.61	0.93	0.93	1.09	1.05
B-3	3.71	0.16	0.37	4.03	4.66	0.00	1.48	4.45	9.89	0.59	1.49	1.29
C-1	4.59	2.74	3.83	11.38	12.67	3.06	0.00	6.12	23.47	1.85	0.01	0.40
C-2	0.21	1.24	1.40	2.46	2.64	1.29	0.86	0.00	4.15	1.12	0.86	0.92
C-3	1.25	0.92	0.87	0.54	0.48	0.91	1.04	1.32	0.00	0.96	1.04	1.03
D-1	7.55	1.04	2.32	11.16	12.67	1.42	2.17	9.34	25.32	0.00	2.18	1.70
D-2	4.56	2.73	3.81	11.31	12.59	3.05	0.01	6.08	23.32	1.85	0.00	0.41
D-3	8.36	3.92	5.74	18.38	20.54	4.46	0.67	10.93	38.62	2.43	0.69	0.00

Values < 0.30 (suggested threshold in [16]) are marked in blue, indicating the resemblance of the corresponding pixel pair.

TABLE III
SIMILARITY AMONG SELECTED PIXELS

	A-1	A-2	A-3	B-1	B-2	B-3	C-1	C-2	C-3	D-1	D-2	D-3
A-1	1.00	0.93	0.90	0.70	0.68	0.67	0.47	0.47	0.47	0.03	0.03	0.03
A-2	0.93	1.00	0.97	0.76	0.75	0.73	0.52	0.52	0.52	0.04	0.03	0.03
A-3	0.90	0.97	1.00	0.79	0.77	0.75	0.54	0.54	0.54	0.04	0.03	0.03
B-1	0.70	0.76	0.79	1.00	0.98	0.97	0.73	0.73	0.73	0.06	0.05	0.05
B-2	0.68	0.75	0.77	0.98	1.00	0.98	0.75	0.74	0.74	0.06	0.05	0.05
B-3	0.67	0.73	0.75	0.97	0.98	1.00	0.76	0.76	0.76	0.06	0.06	0.06
C-1	0.47	0.52	0.54	0.73	0.75	0.76	1.00	0.99	1.00	0.10	0.09	0.09
C-2	0.47	0.52	0.54	0.73	0.74	0.76	0.99	1.00	1.00	0.10	0.09	0.09
C-3	0.47	0.52	0.54	0.73	0.74	0.76	1.00	1.00	1.00	0.10	0.09	0.09
D-1	0.03	0.04	0.04	0.06	0.06	0.06	0.10	0.10	0.10	1.00	0.93	0.93
D-2	0.03	0.03	0.03	0.05	0.05	0.06	0.09	0.09	0.09	0.93	1.00	1.00
D-3	0.03	0.03	0.03	0.05	0.05	0.06	0.09	0.09	0.09	0.93	1.00	1.00

Values > 0.85 are marked in blue, indicating the resemblance status of a pair of pixels.

Figure 1. Time series of unnormalized amplitude values for the twelve selected pixels. The coordinates of each pixel in the GBSAR local coordinate system are given inside the parenthesis after the pixel identifier.

To overcome these limitations, a new similarity measure is proposed to identify siblings. Unlike [16], the developed similarity measure is not based on the interferogram network, but on the mean amplitude over all SLC images. Based on a stack of N SLC images, the similarity measure (denoted as S) between two pixels at (x_1, r_1) and (x_2, r_2) is defined as:

$$S = 1 - |\bar{A}(x_1, r_1) - \bar{A}(x_2, r_2)| / (\bar{A}(x_1, r_1) + \bar{A}(x_2, r_2)), \quad (1)$$

where $\bar{A}(x_i, r_i)$ ($i = 1, 2$) is the mean amplitude of a pixel at (x_i, r_i) over the N SLC images. The proposed similarity measure ranges from zero to one. Larger values imply more resemblance between the pixel pairs. A candidate is considered as a sibling of the current pixel when the similarity between them exceeds a specified threshold. Typical values for the similarity threshold range from 0.85 to 0.95 according to the relevant analysis in Section IV. The proposed similarity measure was tested with the selected samples, with siblings for all pixels detected correctly (Table III). According to the achieved results, it is clear that the proposed similarity provides symmetry and is robust for pixels with sharply different amplitude levels. Moreover, the proposed similarity inherits advantages introduced by [16], including fast computation and low RAM requirements.

Several common hypothesis tests, including the Kolmogorov-Smirnov test [19], the CLT-based test [21], the Anderson-Darling test [15], the paired t -test, and the Wilcoxon signed-rank test (a non-parametric statistical hypothesis test used when comparing two matched samples) [26] were also applied to the selected samples in this study. The significance level for all hypothesis tests was set as 0.05 and the results of the identification of SHPs are illustrated in Figure 2.

Contrary to the result of the developed similarity measure shown in Figure 2(a), hypothesis tests tend to reject three samples of class “A” as heterogeneous. Obviously, the mean amplitude values of three “A-” pixels are different, but relatively close. They are considered as heterogeneous by the applied hypothesis testing methods, but as resembling by the developed similarity measure. This is not a paradox, but symptomatic of a difference between the two types of methods. It reflects that the hypothesis testing techniques are prone to distinguish heterogeneity between pixels with similar mean

amplitude. On the other hand, “B-1”, “B-2” and “C-1” are incorrectly recognized as homogenous pixels by the Anderson-Darling test. For deformation monitoring purposes, performance should be evaluated via coherence estimation and phase filtering.

Figure 2. Identification of resembling or homogenous pixels. Blue grids indicate the homogeneity of the corresponding pixel pair. (a) The proposed similarity. (b) Kolmogorov-Smirnov test. (c) Hypothesis test using CLT. (d) Anderson-Darling test. (e) Paired t -test. (f) Wilcoxon signed-rank test.

B. Estimation of Coherence and Interferometric Phase

The definition of coherence between two zero-mean complex signals, z_1 and z_2 , [27] is:

$$\gamma = \frac{\mathbb{E}(z_1 z_2^*)}{\sqrt{\mathbb{E}(|z_1|^2) \mathbb{E}(|z_2|^2)}} = \rho \cdot e^{i\varphi}, \quad (2)$$

where the operation $\mathbb{E}[\cdot]$ represents the mathematical expectation and the superscript $*$ denotes the complex conjugate operator. ρ is the coherence magnitude and φ is the interferometric phase. In practice, the ensemble average of signals cannot be achieved. The maximum likelihood coherence magnitude $\hat{\rho}$ for a pixel is the magnitude of the coherence estimation $\hat{\gamma}$ (i.e. $\hat{\rho} = |\hat{\gamma}|$), which is computed based on K samples related to the pixel [18, 27]:

$$\hat{\gamma} = \frac{\sum_{l=1}^K z_{1,l} z_{2,l}^*}{\sqrt{\sum_{l=1}^K |z_{1,l}|^2} \sqrt{\sum_{l=1}^K |z_{2,l}|^2}}. \quad (3)$$

In this study, the siblings identified by the developed similarity measure are used as K samples for the estimation of coherence. The siblings-based coherence magnitude $\hat{\rho}$ is further estimated based on the second kind of statistics [24, 25]:

$$\bar{\rho} = \exp\left(\frac{1}{K} \sum_{l=1}^K \ln(\hat{\rho}_l)\right). \quad (4)$$

The coherence magnitude obtained by the second kind statistics is less biased and the variance of the log-estimate is globally lower than that of the regular estimate [24, 25].

In addition, the filtered interferometric phase $\hat{\phi}$ for each pixel is achieved by the non-local averaging of the complex values of its siblings:

$$\begin{cases} e^{i\hat{\phi}} = \sum_{l=1}^K e^{i w_l \phi_l} \\ w_l = \bar{\rho}_l / \sum_{l=1}^K \bar{\rho}_l \end{cases}. \quad (5)$$

III. EXPERIMENTAL RESULTS

A. Overview of Datasets Used in the Study

A MetaSensing FastGBSAR system was used for data collection. The sensor system operates at Ku band with a

wavelength of 17.4 mm and acquisitions can be performed every ten seconds at the finest resolution. The data used in this study was collected by mounting the radar system on a stationary concrete base, continuously observing the cliff on the north side of Tynemouth Priory and Castle, near to Newcastle upon Tyne, UK. The scene mainly comprises the cliff façade, the castle buildings, some areas of beach and the sea close to the south side of King Edward's Bay. An overview of the observed site and the geometric configuration for the data collection is shown in Figure 3(a). A close-up of the surface of the cliff façade can be seen in Figure 3(b), which mainly consists of outcrops, bare earth and vegetation, and a section of an artificial concrete wall. The mean amplitude, corresponding to 60 sequential SLC images, was manually aligned and projected onto the top view of the observed site for a better visual interpretation (see Figures 3(c) and 3(d)). The dimension of each SLC image was 294 by 254 pixels. A mask, displayed in Figure 3(e), was generated by thresholding the mean amplitude image, in which the area of interest (AOI) in white indicates the illuminated region and the background in black corresponds to the shadow zones and sea areas. The background area without useful information should not be considered for precise interferometry analysis. The grey area in the mask was added to mark the ambiguous border between the AOI and the background. The mask was then used for quantitative analysis in Section III-B.

Figure 3. An overview of data collection and the observed site. (a) The deployment of the FastGBSAR system for the data collection. (b) A close-up of the cliff façade with respect to the area marked in red box in (a). (c) The mean amplitude image of 60 GBSAR SLCs (shown in decibels). (d) Co-registration of the mean amplitude image with the top view of the site in Google Earth. (e) An image mask, containing the AOI (in white), the background (in black) and the ambiguous area (in grey) between them.

Based on the same data acquisition configuration, two datasets with different acquisitions and different sampling temporal resolutions were used in the experiments. Dataset I consisted of 60 SLC images and the data acquisition frequency was every 10 seconds. Dataset II consisted of 30 SLC images with a temporal resolution of four minutes.

B. Identification of Siblings

The identification of siblings was performed using the two datasets and results compared to the “FaSHPS” algorithm, namely the identification of SHPs using the CLT-based hypothesis test [21]. The dimension of the non-local search window was fixed to 15 x 15. The similarity threshold for the

proposed method was set as 0.85 and the significance level for the “FaSHPS” hypothesis test as 0.05. It is known that insufficient siblings can lead to inaccuracies in coherence estimation [16] and phase de-noising [13]. If a pixel does not have sufficient siblings within the threshold, a minimum number of siblings are required for the sake of reliable coherence estimation and phase de-noising for this pixel. In such a case the most similar pixels (quantified by the developed similarity measure) beyond the threshold can be added as siblings. On the basis of previous relevant studies [13, 16] and analysis conducted and reported in Section IV, the minimum number of siblings was set as 10. The number of siblings and SHPs for the two datasets are shown in Figure 4. It can be observed that the identified siblings and SHPs in the background area are more than the AOI. This is because the background contains no useful information and suffers from noise. Pixels in the background have similar amplitude statistics contributed by such noise, thus are likely to be siblings or SHPs to each other. The histograms with respect to the number of siblings and SHPs for the AOI area are given in Figure 5. Based on the histograms, it is seen that the overall number of siblings identified by the developed method is greater than the number of SHPs detected by “FaSHPS”, and a large number of isolated pixels without SHPs can also be seen from the histograms of SHPs.

Figure 4. Number of identified resembling pixels. (a) Number of siblings for Dataset I. (b) Number of SHPs for Dataset I. (c) Number of siblings for Dataset II. (d) Number of SHPs for Dataset II.

“FaSHPS” is reported to be computationally efficient when compared with other multitemporal algorithms [21]. The computational efficiency of the developed method, termed “MIAS” (Multi-temporal Interferometry based on Amplitude Similarity), was compared with “FaSHPS” using the same computer with MATLAB R2016b software and an Intel i7 2.40 GHz CPU. For Dataset I with 60 SLCs, “MIAS” cost 0.9 s completing the identification process, while “FaSHPS” cost 9.1 s. The time costs of Dataset II with 30 SLCs was 0.8 s for “MIAS” and 7.6 s for “FaSHPS”.

Figure 5. Histograms of siblings and SHPs in the AOI for two datasets. $\bar{N}_{\text{siblings}}$ and $\bar{N}_{\text{SHPs}}$ are the average number of siblings and SHPs respectively. $N_{\text{siblings}=0}$ and $N_{\text{SHPs}=0}$ represent the number of isolated pixels without siblings or SHPs respectively. (a) Histogram of siblings for Dataset I. (b) Histogram of SHPs for Dataset I. (c) Histogram of Siblings for Dataset II; (d) Histogram of SHPs for Dataset II.

C. Coherence Estimation

Two GBSAR interferometric pairs were utilised in the experiments for coherence estimation. One interferogram was constructed by two temporally consecutive SLC images in Dataset I, with a time difference between the two acquisitions of 10 s. The second interferogram was constructed from two SLC images with a 2-hour interval from Dataset II. The coherence for the two interferometric pairs was obtained by the following methods: the “boxcar” estimator, the “nl-InSAR” technique, the direct SHPs-based estimator (denoted as “SHPs-based”), the direct siblings-based (denoted as “Siblings-based”), the SHPs-based estimation with the second kind statistics (denoted as “SHPs+Sec”) and the improved siblings-based coherence estimation with the second kind statistics (denoted as “Siblings+Sec”). Note that “SHPs+Sec” is the coherence estimation algorithm proposed in “FaSHPS” and “Siblings+Sec” is the developed coherence estimation method in this study. The coherence maps for the interferogram with short time difference are shown in Figure 6.

In comparison to all non-local methods, it is visible that the “boxcar” estimator tends to overestimate the coherence in the background and suffer resolution losses in the AOI. The findings are consistent with previous spaceborne SAR studies [15, 16]. The coherence maps in Figures 6(d) and (f) achieved based on the second kind statistics are visibly smoother than the direct non-local estimation in Figures 6(c) and (e).

To quantitatively compare the performance of these methods, the mean and standard deviation of the coherence for the AOI and the background were calculated. Moreover, the number of pixels in the AOI and the background with coherence greater than a specified threshold value was recorded. The background, consisting of shadow zones and sea areas, was dominated by high noise and was expected to show low coherence. Thus, a greater number of coherent pixels in the background means a

lower performance of the method in coping with GBSAR signal noise. These statistics are summarised in Table IV.

Figure 6. The coherence maps of the interferogram with a 10 s time interval from Dataset I. (a) “Boxcar” (5×5 window). (b) “nl-InSAR” (search window: 21×21, patch window: 7×7, minimum equivalent number of looks: 10, number of iterations: 10). (c) “SHPs-based”. (d) “SHPs+Sec”. (e) “Siblings-based”. (f) “Siblings+Sec”.

TABLE IV
THE STATISTICS OF THE COHERENCE FOR THE INTERFEROGRAM WITH TEN SECONDS ELAPSE

	AOI			Background		
	mean	std ^a	pixels	mean	std	pixels
Boxcar	0.82	0.17	8,480 ($\gamma > 0.6$)	0.33	0.17	3,559 ($\gamma > 0.6$)
nl-InSAR	0.80	0.18	8,189 ($\gamma > 0.6$)	0.17	0.13	950 ($\gamma > 0.6$)
SHPs-based	0.83	0.22	7,905 ($\gamma > 0.6$)	0.14	0.09	216 ($\gamma > 0.6$)
SHPs+Sec	0.82	0.22	7,808 ($\gamma > 0.6$)	0.12	0.07	105 ($\gamma > 0.6$)
Siblings-based	0.70	0.22	8,064 ($\gamma > 0.45$)	0.13	0.08	131 ($\gamma > 0.45$)
Siblings+Sec	0.67	0.14	8,031 ($\gamma > 0.45$)	0.12	0.05	4 ($\gamma > 0.45$)

^astd is the standard deviation of the estimated coherence.

The overestimation of the “boxcar” coherence for the decorrelated area was again confirmed by the high mean and standard deviation values and the large amount of false coherence in the background. The “nl-InSAR” approach obtains high coherence in the AOI but with too many false coherent pixels in the background. Overall, SHPs or sibling-related coherence estimation methods were more robust to the noisy background than “boxcar” and “nl-InSAR”. In particular, the methods based on the second kind statistics can significantly mitigate the false coherence estimation in the background. The overall sibling-related coherence in the AOI was lower than

other methods. Thus, a different threshold value was used for the statics of “Siblings-based” and “Siblings+Sec”. From Table IV, it can be observed that the number of false coherent pixels detected by the developed method (“Siblings+Sec”) was much less than that of other methods, indicating the best performance in this experiment. Furthermore, the coherence estimation was also conducted for the second interferogram with a two-hour interval. Figure 7 displays coherence maps and Table V compares the statistics in the AOI and the background.

Figure 7. Coherence of the interferogram with a two-hour interval from Dataset II. (a) “Boxcar”. (b) “nl-InSAR”. (c) “SHPs-based”. (d) “SHPs+Sec” (the decorrelated area caused by the sea level rise is roughly marked in the black box). (e) “Siblings-based”. (f) “Siblings+Sec”.

TABLE V
COHERENCE STATISTICS FOR THE INTERFEROGRAM WITH TWO HOURS ELAPSE

	AOI			Background		
	mean	std	pixels	mean	std	pixels
Boxcar	0.51	0.24	3,444	0.31	0.15	1,875
nl-InSAR	0.52	0.25	3,516	0.14	0.10	365
			($\gamma > 0.6$)			($\gamma > 0.6$)
SHPs-based	0.51	0.30	3,567	0.12	0.07	44
			($\gamma > 0.6$)			($\gamma > 0.6$)
SHPs+Sec	0.48	0.29	3,083	0.11	0.04	19
			($\gamma > 0.6$)			($\gamma > 0.6$)
Siblings-based	0.34	0.22	2,575	0.12	0.06	12
			($\gamma > 0.45$)			($\gamma > 0.45$)
Siblings+Sec	0.31	0.19	1,973	0.10	0.04	3
			($\gamma > 0.45$)			($\gamma > 0.45$)

Comparison of the coherence maps shown in Figures 6 and 7, it is evident that the 2-hour interferogram suffers temporal decorrelation. As mentioned previously, FastGBSAR works at Ku band and the short wavelength is sensitive to surface changes and atmospheric variations. The vegetation coverage on the illuminated cliff façade aggregates the decorrelation.

Moreover, decorrelation on the left part of the AOI that is roughly marked by the black box in Figure 7(d) was likely caused by the tide that submerged the beach and rocks close to the sea over the course of the two-hour interval. The temporal decorrelation also demonstrates the requirement for GBSAR time series analysis.

According to the experimental results, the coherence statistics (including the mean, standard deviation and coherence amounts) in the AOI achieved by “Siblings-based” and “Siblings+Sec” are lower than the counterparts of “SHPs-based” and “SHPs+Sec”, which is related to the fact that the number of siblings identified by the proposed “MIAS” was greater than the number of SHPs detected by “FaSHPS”. There are a number of isolated pixels without SHPs detected by “FaSHPS” and the coherence for an isolated pixel is always one [19] as coherence in this case is estimated merely using two complex pixel values (one on the master and the other on the slave). Reported in [16, 18], the estimation with insufficient samples would produce a biased result.

Table V shows that “SHPs-based” and “SHPs+Sec” selected more coherent pixels in the AOI than “Siblings-based” and “Siblings+Sec”. However, some coherent pixels selected by “SHPs-based” and “SHPs+Sec” can actually be decorrelated in the left part of the AOI. To explain this, assume a pixel in the left part of the AOI, which corresponds to a ground rock close to the sea, was visible in the master image but was submerged by water two hours later and became invisible in the slave image. The pixel should be decorrelated with a low coherence value in the 2-hour interferogram. However, this target is prone to be an isolated pixel with high coherence in “FaSHPS”, as hypothesis tests tend to reject samples with a strong reflection as heterogeneous. A number of this kind of submerged isolated target were de-correlated but still showed high coherence in the two-hour interferogram. This can be confirmed by the discontinuous interferometric phase of coherent pixels selected by “SHPs+Sec”, shown in Figure 9. On the other hand, the proposed method obtained the least number of false coherent pixels. In the proposed method, a minimum number of ten siblings were kept. Admittedly, the coherence of an isolated scatterer surrounded by distributed scatterers would be degraded in this case. Experimental results demonstrate that maintaining a minimum number of siblings is able to reduce the bias in coherence estimation, which was also reported in previous studies [16, 18].

D. Phase Filtering

Coherence is an indicator of the interferometric phase quality. Usually, the deformation measurement only focuses on coherent pixels. Thus, filtering is further carried out to increase the SNR of the interferometric phase for coherent pixels. To validate the feasibility of the developed non-local method on phase filtering, experiments were conducted using the two interferograms introduced previously. The results achieved by the developed method were compared with results from the “boxcar” multilooking, the “nl-InSAR” and the SHPs-based filtering method. Pixels for each filtering process were separately detected by their own coherence. Only pixels with

coherence above the specified threshold values were processed. The performance of filtering methods can be indicated by Quality Factor (denoted as Q) [28]. Q for the original image before filtering always equals to one. Any shift in the mean value of the interferometric phase before and after filtering will decrease Q and be evaluated as degradation in filter capability. A reduction of the standard deviation of the interferometric phase will increase Q . A higher Q value implies a better performance of the filtering technique. Thus, the quality factor Q is used to quantitatively compare the performance of these filtering methods.

For the interferogram formed by two sequential acquisitions with only ten seconds time difference, an assumption is that no significant surface movements took place and the atmospheric conditions remained relatively stable over such a short period. Accordingly, the phase change of coherent pixels should be close to zero. The wrapped interferometric phase of coherent pixels and phase histograms before and after filtering for this interferogram are given in Figure 8. Q values achieved by different methods are annotated to the phase histograms in Figure 8.

Figure 8. Filtering results for the interferogram with ten seconds elapse. (First line) The original wrapped interferogram. (Following lines) (a) the interferometric phase of coherent pixels before filtering; (b) the filtered interferometric phase, and (c) phase histograms and the filtering quality factor, obtained by (top to bottom) the “boxcar” multilooking (5×5 window), the “nl-InSAR”, the SHPs-based filtering and the developed siblings-based filtering. Correspondingly, coherent pixels are respectively determined by the “boxcar” estimation ($\gamma > 0.6$), “nl-InSAR” ($\gamma > 0.6$), “SHPs+Sec” ($\gamma > 0.6$) and “Siblings+Sec” ($\gamma > 0.45$). Pixels in decorrelated areas are marked in brown for the convenience of visualization.

Figure 9. Filtering results for the 2-hour interferogram. The implication of subfigures is as for Figure 8. Pixels in de-correlated areas are marked in brown for the convenience of visualization.

From the phase histograms in Figure 8(c), it can be seen that the mean values of the interferometric phase in the coherent areas before and after filtering are close to zero. This supports the assumption that no significant surface movements and environmental variations occurred during the short time elapse in the observed area. Among the four filtering methods, the developed siblings-based filtering achieved the best Q values (22.82), followed by “boxcar” multilooking (10.97), nl-InSAR (2.88) and SHPs-based filtering (1.14).

The number of pixels with an absolute phase change greater than $\pi/3$ were also recorded. A larger number implies a poorer filtering performance under the assumption of no significant surface movements and environmental variations. The values for “boxcar”, “nl-InSAR”, the SHPs-based filtering and the developed siblings-based filtering were 6, 16, 145 and 1 respectively. Similarly, the developed siblings-based filtering outperformed other methods based on this experiment and the SHPs-based filtering obtained a large number of pixels with an absolute phase change greater than $\pi/3$. To discern the reason, the average number of detected SHPs and siblings for all 145 pixels was calculated. A striking contrast between the two values was witnessed: the average SHPs was 0.9 while the average siblings was 37.4. This finding agrees with previous studies [16, 19] that maintaining a minimum number of resembling samples can facilitate spatial filtering and coherence estimation. The SHPs-based method was able to distinguish heterogeneity and lead to a large number of isolated pixels, this,

however, may bring problems in phase filtering. It is worth noting that the “FaSHPS” algorithm was originally proposed only for coherence estimation. These findings were also verified by the experimental results for the 2-hour interferogram, as shown in Figure 9. The overall performance of different methods for this interferometric pair with a longer time elapse was similar to that with a shorter time elapse. The developed siblings-based filtering showed good filtering performance with a Q factor reaching 9.41, which was much higher than the other techniques.

E. Time Series Analysis

Interferograms suffering from temporal decorrelation will have limited use for deformation monitoring. The interferogram with a two-hour interval in this study displayed temporal decorrelation. Time series analysis is thus proposed to overcome this limitation. The developed non-local method was integrated with a GBSAR time series analysis chain based on the SBAS algorithm. As datasets were acquired continuously with a zero-baseline, only the temporal baseline was considered in this analysis. Specifically, a temporal baseline constraint was set to construct the redundant interferogram network. The coherence of each interferogram in the network was calculated by the developed method, namely the siblings-based coherence with the estimation of the second kind statistics. Coherent pixels were detected via the criterion presented in [29], which enables the selection of not only qualified partially coherent pixels, but also persistent scatterers. Further analysis and interpretation is then conducted only on the detected coherent pixels. The interferometric phase of detected pixels was firstly de-noised using the non-local filter. The unwrapped phase of detected pixels was then obtained using the Minimum Cost Flow approach [30]. Thereafter, the least-squares solution for each pixel can be achieved in the time series estimation using only the coherent phase of this pixel. The inverted result is the superposition of the surface displacements and the atmospheric variations. Thus, atmospheric artefacts must be properly compensated in order to obtain precise displacement time series. Considering the moderate size of the test site, the atmospheric variation was modelled as a range-dependent model through highly-coherent pixels selected from stable areas and under the medium homogeneity hypothesis, referring to the approach presented in [31].

In the experiments, the temporal baseline constraints were set as one minute for Dataset I and 20 minutes for Dataset II, with consideration for the computational efficiency and temporal decorrelation. Thus, there were 339 interferograms for Dataset I and 135 for Dataset II. A full combination of interferograms can provide the most redundant observations, but it also increases the computation load and degrades the real-time performance in urgent situations. Parameter configurations were kept the same for both datasets: the similarity threshold was set to 0.85; the minimum number of siblings was set to 10; the non-local window size was 15 x 15 pixels and the coherence threshold value was 0.45. A subset of highly-coherent pixels with mean coherence over all interferograms of > 0.85 was selected from stable areas to perform the linear regression of

atmospheric variations (i.e. $y = a_0 + a_1x$, where y denotes the atmospheric variation and x the range between the radar sensor and the coherent target; a_0 and a_1 are coefficients). The stable areas can be identified through a priori knowledge and visual inspection of the superposition map of atmospheric variations and displacements. Based on the linear range-dependent model, the atmospheric variations of all coherent pixels were compensated and thus separated from the cumulative displacements.

Regarding Dataset I, the correction of atmospheric variations and the obtainment of cumulative displacements are given in Figure 10. The superposition map of atmospheric variations and displacements in Figure 10(a) can be used as an auxiliary visual material to identify stable areas. According to Figures 10(b) and 10(c), it appeared that the atmospheric conditions remained relatively stable during the 10-minute observation period. However, obvious deformation signals can be observed in three areas (Figure 10(d)). These areas are near the sea and the ground targets are mainly rocks and sands. To investigate these signals, three pixels (P1, P2 and P3) were selected to look into their temporal evolution. A stable pixel (P4) was also selected as a comparison. The line graphs in Figure 10(c) show the time series of the SLC raw phase (ψ), the one-dimensional unwrapped phase (φ_{1D}) and cumulative displacements (d) for these pixels. Particularly, φ_{1D} is a vector of temporally unwrapped phase on interferograms formed with the first (earliest) SLC as the master and others as slaves. It is worth noting that φ_{1D} is not the phase used in time series analysis and it is only used here as an auxiliary evidence of the high phase quality and the rough change trend of these pixels. In general, pixels P1, P2, and P3 experienced a gradual process of change. The overall trend of cumulative displacements agreed with the trend of φ_{1D} . On the other hand, there is inconsistency in scale as φ_{1D} is likely to have unwrapping errors and it is not the unwrapped phase used in time series analysis. Moreover, non-local filtering and atmospheric estimation also altered the principal value of the interferometric phase used for deformation derivation. Without proper validation data, it is difficult to identify these signals, but it is likely to be gradual movements of some ground targets near the sea.

The results of Dataset II are shown in Figure 11. It can be observed that pixels P1 and P3 in Figure 10(d) disappeared from the results of Dataset II. This is because the first image of Dataset II was acquired at around midday and the last one was captured two hours later. During that time, the areas where P1 and P3 were located became submerged due to the sea tide. Besides, the linear trend between the atmospheric variation and the range is visible in Figure 11(b). The superposition (Figure 11(a)) is dominated by the atmospheric variation (Figure 11(c)). From the deformation map in Figure 11(d), no significant signals can be found in the cliff façade or the castle buildings as the cumulative displacements at these areas vary within 2 mm. Similar to Dataset I, deformation signals appeared in the areas near the sea, and pixels P2 and P5 experienced approximate displacements of 3.5 mm while P4 remained stable over the two-hour observation period (Figure 11(e)).

Figure 10. GBSAR time series analysis results of Dataset I. (a) The superposition map of displacements and atmospheric variations. (b) Linear regression of atmospheric variation. (c) Atmospheric variation map over 10 minutes of the acquisition time. (d) Co-registration of the displacement map with the top view of the site in Google Earth. (e) The time series raw phase, 1D unwrapped phase and cumulative displacements of the four pixels.

IV. DISCUSSION

The performance of the developed non-local method on coherence estimation and phase filtering has been demonstrated and evaluated. In this section, the focus is on justification of parameters involved in the developed non-local method: the similarity threshold, the coherence threshold, the non-local window size and the minimum siblings. Based on Dataset II, different combinations of these parameters were used in time series analysis. The number of detected coherent pixels, the root mean square (RMS) of inversion precision (defined in Appendix A) for all coherent pixels and the time cost is recorded in Table VI.

By comparing Configurations 1 - 8, it is found that the similarity threshold affects the number of coherent pixels. Particularly, Configurations 5 - 8 show that a higher similarity increases the number of highly-coherent pixels ($\gamma > 0.85$) and degrades the precision. This is because a higher similarity threshold means fewer siblings, which leads to the more computational efficiency and the less smoothness in the coherence estimation and interferometric phase. Meanwhile, a too low similarity threshold should also be avoided as it would

Figure 11. GBSAR time series analysis results of Dataset II. (a) The superposition map of displacements and atmospheric variations over two hours of the acquisition time. (b) Linear regression of atmospheric variation. (c) The atmospheric variation map over two-hour acquisition time. (d) The displacement map co-registered with the top view of the site in Google Earth. Note that the coverage of this displacement map is smaller than that of Dataset I due to sea tides. (e) The time series atmospheric variations (d_{atm}) and cumulative displacements of pixels P2, P4 and P5.

TABLE VI
RESULTS OF DIFFERENT PARAMETER CONFIGURATIONS IN GBSAR TIME SERIES ANALYSIS

	S_{thr}^a	M_{sib}^b	γ_{thr}^c	W^d	n_{CPS}^e	RMS ^f	t^g
1	0.8	10	0.85	15×15	417	0.06 mm	310 s
2	0.85	10	0.85	15×15	469	0.06 mm	283 s
3	0.9	10	0.85	15×15	540	0.07 mm	267 s
4	0.95	10	0.85	15×15	595	0.08 mm	211 s
5	0.8	10	0.45	15×15	5,312	0.12 mm	304 s
6	0.85	10	0.45	15×15	5,283	0.14 mm	300 s
7	0.9	10	0.45	15×15	5,441	0.16 mm	277 s
8	0.95	10	0.45	15×15	5,867	0.21 mm	211 s
9	0.85	10	0.35	15×15	7,520	0.18 mm	297 s
10	0.85	10	0.55	15×15	3,429	0.10 mm	296 s
11	0.85	10	0.45	11×11	5,630	0.18 mm	206 s
12	0.85	10	0.45	19×19	5,120	0.12 mm	378 s
13	0.85	5	0.45	15×15	5,312	0.15 mm	277 s
14	0.85	5	0.85	15×15	511	0.06 mm	275 s
15	0.85	25	0.45	15×15	5,226	0.13 mm	276 s
16	0.85	25	0.85	15×15	363	0.05 mm	272 s

^a S_{thr} is the similarity threshold; ^b M_{sib} is the number of minimum siblings; ^c γ_{thr} is the coherence threshold; ^d W is the window size; ^e n_{CPS} is the number of coherent pixels; ^fRMS is the root mean square of inversion precision; ^g t is the time cost.

detect too many inaccurate siblings. Figure 12 compares the effect of the similarity threshold on coherence estimation. A low similarity threshold leads to serious resolution loss.

Configurations 2, 6, 9 and 10 demonstrate that a lower coherence threshold value can enlarge the number of coherent pixels at the expense of precision. Based on Configurations 2, 11 and 12, it is clear that the non-local window size has a considerable effect on computation efficiency. A small window size is efficient but may have limited ability in phase denoising. In addition, maintaining more siblings will also degrade coherence estimation, especially for highly-coherent pixels in the areas with rich texture according to Configurations 2, 6 and 13 - 16. On the other hand, too few siblings would cause issues in phase filtering, which has been reported in the experiments. The parameter configuration is therefore a trade-off between characteristics.

Figure 12. Coherence estimation by the developed method with different similarity threshold values. (a) Thresholding by 0.85. (b) Thresholding by 0.6.

V. CONCLUSIONS

This study has proposed a simple but efficient similarity measure to identify resembling pixels for distributed targets and presented a comprehensive non-local method (“MIAS”) based upon this concept. The accurate estimation of coherence and interferometric phase can be achieved by the developed method and has been integrated into a complete GBSAR time series analysis. The following conclusions are reached on the basis of the experimental results and related analysis:

- (1) The feasibility of the developed similarity on the identification of resembling samples from a non-local window has been verified by using a number of selected pixels. The proposed similarity measure overcomes the limitations of existing methods on processing FastGBSAR datasets and extracts all test samples correctly.
- (2) Experiments have been performed with two FastGBSAR datasets. It has been successfully demonstrated that the identification process of the proposed “MIAS” method is more efficient and faster than the “FaSHPS” algorithm.
- (3) Qualitative and quantitative analysis has been conducted to assess the performance of “MIAS” on coherence estimation and phase filtering. “MIAS” can largely mitigate the coherence estimation bias and avoid overestimating the decorrelated area without the cost of resolution. The non-local means filtering based on the identified siblings achieves a high quality factor in de-noising the interferometric phase.
- (4) The integration of the proposed “MIAS” into a complete GBSAR time series analysis demonstrates the potential of “MIAS” in continuous deformation monitoring, thereby facilitating a range of applications for which GBSAR interferometry is suited.

Although the experimental datasets were acquired with only short-term observation periods, the combination of the

proposed non-local method and the SBAS algorithm is potentially suitable for GBSAR acquisitions for long-term observation periods as long as coherence exists between acquisitions with small temporal baselines. It is also worth noting that the developed non-local method can produce accurate results for coherence estimation and phase filtering but it may have limited use in low coherent areas, such as natural slopes with thick vegetation coverage. Decorrelation becomes a serious issue in this case due to the short-wavelength character of a typical GBSAR system, thus hampering the reliable use of microwave interferometry. Deformation monitoring in low coherent areas can, however, be achieved using artificial corner reflectors [32]. The application of the developed approach to discontinuous GBSAR acquisitions of long-term periods will be addressed in the future work.

APPENDIX A: INVERSION PRECISION

The goal of InSAR time series analysis for deformation monitoring is to obtain the deformation time series. The mean velocity between time-adjacent acquisitions is a preferable choice in the InSAR time series analysis to avoid large discontinuities in cumulative deformations and to obtain a physically sound solution [33, 34]. Accordingly, the prerequisite is to obtain the incremental time series of phase change between time-adjacent acquisitions. We assume a redundant network of L interferograms formed by N SLC images. Each pixel is associated with a system in the following matrix representation:

$$\mathbf{B}_{L \times N} \boldsymbol{\Phi}_{N \times 1} = \boldsymbol{\delta} \boldsymbol{\Phi}_{L \times 1} + \boldsymbol{\varepsilon}_{L \times 1}, \quad (\text{A.1})$$

where $\mathbf{B}$ is the coefficient matrix; $\boldsymbol{\Phi}$ is the matrix containing the incremental time series of phase change with respect to the superposition of both displacement and atmospheric variation; $\boldsymbol{\delta} \boldsymbol{\Phi}$ is the matrix of redundant unwrapped interferometric phase; $\boldsymbol{\varepsilon}$ is the noise matrix. With redundant interferometric phase, the optimal estimation of the incremental time series of phase change $\hat{\boldsymbol{\Phi}}$ for each pixel can be performed based on equation (A.1) via any appropriate solvers (e.g. singular value decomposition, normal least squares). The phase residuals in the inversion are:

$$\mathbf{V}_{L \times 1} = \mathbf{B}_{L \times N} \hat{\boldsymbol{\Phi}}_{N \times 1} - \boldsymbol{\delta} \boldsymbol{\Phi}_{L \times 1}. \quad (\text{A.2})$$

The root mean square of phase residuals for a pixel is:

$$\sigma_0 = \sqrt{\frac{\mathbf{V}^T \mathbf{V}}{r}} = \sqrt{\frac{\mathbf{V}^T \mathbf{V}}{n - N + 1}}, \quad (\text{A.3})$$

where r is the number of redundancies and n is the number of coherence occurrences in the redundant network. Accordingly, the covariance matrix of the estimated $\hat{\boldsymbol{\Phi}}_{N \times 1}$ can be calculated by:

$$\mathbf{D}_{\hat{\boldsymbol{\Phi}} \hat{\boldsymbol{\Phi}}} = \sigma_0 \sqrt{(\mathbf{B}^T \mathbf{B})^{-1}}. \quad (\text{A.4})$$

As the final cumulative displacement is obtained by removing atmospheric variation from the sum of them, we introduce an estimator $\hat{d}$ which is the sum of the cumulative displacement and atmospheric variation between the first image and the last image:

$$\hat{d} = -\frac{\lambda}{4\pi} \sum_{k=0}^{N-1} (\hat{\phi}_{t_k t_{k+1}}^{dis} + \hat{\phi}_{t_k t_{k+1}}^{atm}) = \mathbf{F}_{1 \times N} \hat{\boldsymbol{\Phi}}_{N \times 1}, \quad (\text{A.5})$$

where $\mathbf{F} = [-\lambda/4\pi \quad \cdots \quad -\lambda/4\pi]$. The theoretical precision of $\hat{d}$ is used as the precision indicator in the estimation for each pixel, which is calculated by:

$$\sigma_{\hat{d}} = \sqrt{D_{\hat{d}}} = \sqrt{\mathbf{F} \mathbf{D}_{\Phi\Phi} \mathbf{F}^T}. \quad (\text{A.6})$$

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