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Persistent Scatterer densification through the application of Capon and APES based SAR reprocessing algorithms.

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Abstract—Capon’s minimum-variance method (MVM) and Amplitude and Phase Estimation (APES) spectral estimation algorithms can be applied to SAR processing to improve the resolution and suppress sidelobe levels. In this paper, we use Capon/APES based SAR reprocessing algorithms to increase the Persistent Scatterer (PS) density in Persistent Scatterer Interferometry (PSI). We propose a Persistent Scatterer Candidate (PSC) selection algorithm applicable to the super-resolution reprocessed images and the corresponding processing chain. The performance of the proposed algorithm is evaluated by a number of simulations and a stack of TerraSAR-X data. The results show that the Capon algorithm outperforms others in PSC selection. We present a full PSI time-series analysis on the PSCs extracted from the Capon reprocessed stacks. The results show that the PS density is increased between 50% and 60%, while their interferometric quality is maintained.

Index Terms—Super-Resolution, Capon, APES, PS density, PSI

I. INTRODUCTION

PERSISTENT SCATTERER INTERFEROMETRY (PSI) is a powerful remote sensing technique that allows the detection and estimation of relative surface deformations with accuracies in the order of mm/year. One of the key performance indicators in PSI is the Persistent Scatterer (PS) density since a high PS density allows the retrieval of very localized deformation signals and also leads to more robust network solutions. Because of this, users of PSI techniques often rely on the use of very high-resolution data generated by missions such as TerraSAR-X [1], [2] and Cosmo-Skymed [3], [4]. This paper explores the application of super-resolution methods based on adaptive spectral estimation techniques to increase the PS density.

Traditional PSI algorithms select Persistent Scatterer Candidate (PSC) points from focused Single Look Complex (SLC) stacks. Generally, SLC images are generated from SAR raw data, for which a variety of algorithms can be applied, such as range-Doppler algorithms [5], chirp-scaling algorithms [6], [7], wave-number focusing algorithms [8]. These focusing algorithms are computationally efficient approximations to a matched-filter, where the spatial resolution is inversely proportional to the available or processed signal-bandwidth. We

will refer to conventionally processed SLC images as Fourier-based images. Fourier-based imaging results in a constant, and thus predictable, resolution and a relatively high sidelobe level, which can only be improved by trading resolution for ambiguity suppression [9].

Several authors have shown that modern spectral estimation algorithms can be applied to SAR focusing, thereby improving the resolution and reducing the sidelobe levels [9], [10]. Although a wide range of spectral estimation algorithms can be applied in SAR, we limit our discussion to non-parametric approaches, and in particular to Capon’s minimum-variance method (MVM) and the Amplitude and Phase Estimation (APES) method. This avoids making assumptions about the data (e.g. setting a maximum number of dominant scatterers), therefore avoiding model errors [11]. We will refer to Capon and APES methods as Super-Resolution (SR) algorithms considering that the resolution is improved by reprocessing.

For conventional PSI processing, PSCs are typically selected by setting an upper limit on their normalized amplitude dispersion [12], which has been shown to be a good indicator of phase stability when a sufficient number of SAR images (>30) are available. The amplitude-dispersion selection process is usually followed by a sidelobe filtering step [13], [14], [15]. There is, of course, a trade-off between the PSC density and the normalized amplitude dispersion threshold. This trade-off is, however, beyond the scope of this paper.

Adapting the PSC selection process to a super-resolution scenario is one of the main challenges that we address in this paper. The resolution achievable by super-resolution processing algorithms depends on the statistical properties of the scene and is, therefore, spatially variant. The required grid spacing of the refocused SAR images is determined by the finest achieved resolution [10]. Consequently, most observed targets are highly over-sampled, causing the traditional PSC selection algorithm to select pixel clusters rather than single pixels for each PSC. This paper introduces a PSC selection approach suitable to SR reprocessed images. A second issue arising from SR processing is jitter of the intensity-peak positions, which can be caused, for example, by thermal noise. This jitter is also present in Fourier-based images, but in that case, it is small compared to the resolution. To deal with the spatial variability of the resolution, only the pixels whose amplitudes are local peaks on the average amplitude images are selected as initial PSCs. To tackle peak jitter, peak matching is implemented. The normalized amplitude dispersion and the noise threshold are also used as criteria.

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We also propose a processing chain that integrates Capon/APES spectral estimation algorithms into PSI. The whole chain is referred to as SR-PSI. We simulated a number of SAR images with varied point scatterer density and employed SR-PSI. We used False Rejection Rate (FRR) and False Acceptance Rate (FAR) as two main benchmarks to evaluate the performance. In order to evaluate the performance of the selected algorithms on real data, We also applied SR-PSI to TerraSAR-X data of Rotterdam, the Netherlands and compared PSCs of SR-PSI with those of conventional PSI processing. We imported the PSCs extracted from the Capon reprocessed images into DePSI [16] and obtained the deformation velocities of the PSs. Subsequently, we compare the performance of the PSs.

Section II reviews the Capon/APES based SAR reprocessing theory. This section also introduces a PSC selection algorithm that can be applied to Capon/APES reprocessed SAR images. Section III presents the SR-PSI workflow. Section IV discusses a number of numerical simulations for a range of conditions, followed by the implementation of SR-PSI and the traditional algorithm. Subsequently, the performance is discussed by using FRR and FAR as benchmarks. Section V presents results obtained applying SR-PSI to actual TerraSAR-X data. Finally, Section VI summarizes the main findings of our work.

II. FORMULATION

A. Capon/APES based SAR reprocessing

A detailed discussion of Capon and APES based reprocessing theory can be found in [10]. For the sake of completeness, here we review the main aspects.

Traditionally, a matched-filter approach is applied to raw SAR data to generate SLC images. The SLC image in the frequency domain is given by

$$S(f_r, f_a) = Z(f_r, f_a) \cdot P^*(f_r, f_a), \quad (1)$$

where $Z(f_r, f_a)$ and $P(f_r, f_a)$ are the 2-D Fourier transform of the received signal and the point-target response, respectively, and $(\cdot)^*$ denotes complex conjugate operator. Using the shift property of the Fourier transform, the received signal can be presented as

$$Z(f_r, f_a) = \sum_{i=0}^{M-1} a_i \cdot P(f_r, f_a) \cdot e^{-j2\pi(t_{ri} \cdot f_r + t_{ai} \cdot f_a)}, \quad (2)$$

where M is the number of scatterers, t_{ri} , t_{ai} are the temporal delay along range and azimuth and a_i is the complex-valued scattering coefficient. Substituting (2) into (1), gives

$$S(f_r, f_a) = \sum_{i=0}^{M-1} a_i \cdot |P(f_r, f_a)|^2 \cdot e^{-j2\pi(t_{ri} \cdot f_r + t_{ai} \cdot f_a)}, \quad (3)$$

which shows that the frequency domain expression of the Fourier-based image is the sum of 2-D complex harmonic functions, multiplied by the complex-valued scattering coefficient of each scatterer, windowed by the spectral density function of the point-target response. We can now understand the SAR imaging process as an attempt of estimating the sets of scattering coefficients a_i and range and azimuth delay

for each scatterer, which is actually a spectral component estimation problem. Taking the inverse Fourier transform of (3) in order to obtain $s(t_r, s_r)$ can be considered as the most straightforward spectral estimation, but we can apply virtually any spectrum estimation method. In this paper, we apply Capon/APES algorithms.

Both Capon and APES belong to the so-called nonparametric adaptive filter-bank methods [17]. They construct FIR (Finite Impulse Response) filters that pass the expected frequency without distortion and, at the same time, attenuates all the other frequencies *as much as possible*. The *super-resolution* comes from the ability of the algorithms to place a null, suppressing spectral spillover from nearby objects [10].

Let $X(n_1, n_2)$ be a 2-D data matrix of dimension $N_1 \times N_2$. $X(n_1, n_2)$ can be divided into an ensemble of $L_1 \times L_2$ overlapping sub-matrices of $M_1 \times M_2$ elements each. Different authors have found that maximal overlap provides the best results in the implementation of Capon and APES, thus $L_1 = N_1 - M_1 + 1$ and $L_2 = N_2 - M_2 + 1$. Let us define snapshots $\mathbf{z}_{l_1, l_2}$ as the vectorization of sub-matrices of $X(n_1, n_2)$:

$$\mathbf{z}_{l_1, l_2} = \text{vec} \left(\begin{bmatrix} X(l_1, l_2) & \dots & X(l_1, l_2 + M_2 - 1) \\ \vdots & \ddots & \vdots \\ X(l_1 + M_1 - 1, l_2) & \dots & X(l_1 + M_1 - 1, l_2 + M_2 - 1) \end{bmatrix} \right), \quad (4)$$

where $l_1 = 0, \dots, L_1 - 1$ and $l_2 = 0, \dots, L_2 - 1$. Capon's algorithm and APES need an estimate of the true covariance matrix, $\mathbf{R}$, for which the sample covariance matrix can be used. This sample covariance matrix is given by

$$\hat{\mathbf{R}} = \frac{1}{L_1 L_2} \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} \mathbf{z}_{l_1, l_2} \mathbf{z}_{l_1, l_2}^H, \quad (5)$$

where $(\cdot)^H$ denotes conjugate transpose operator.

The Capon filters are designed so that the power of the filtered signal is minimized with the constraint that the gain of the filter remains one at the selected frequency [18]. The Capon filter is the solution of the following minimization problem:

$$\min_{\mathbf{h}} \mathbf{h}^H \mathbf{R} \mathbf{h}, \text{ subject to } \mathbf{h}^H \mathbf{a} = 1, \quad (6)$$

where $\mathbf{R}$ is the covariance matrix, $\mathbf{a}$ is the 2-D Fourier matrix and $\mathbf{h}$ is the constructed filter vector.

In the case of APES, the filter output is required to resemble a sinusoid with frequency ω_1, ω_2 as close as possible [19]. Mathematically, this is expressed as solving the minimization problem

$$\min_{\mathbf{h}} \frac{1}{L_1 L_2} \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} |\mathbf{h}^H \mathbf{z}_{l_1, l_2} - \alpha(\omega_1, \omega_2) e^{j(\omega_1 l_1 + \omega_2 l_2)}|, \quad (7)$$

subject to $\mathbf{h}^H \mathbf{a} = 1$.

After constructing the filter from (6) or (7) and applying Least Square, the spectral estimate, which in our case is a super-resolved image, is given by

$$s(\omega_1, \omega_2) = \frac{1}{L_1 L_2} \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} \mathbf{h}^H \mathbf{z}_{l_1, l_2} e^{j(\omega_1 l_1 + \omega_2 l_2)}, \quad (8)$$

where both $\mathbf{h}$ and $\mathbf{z}$ are $M_1 \times M_2$ vectors.

Fig. 1. Illustration of the adaptive resolving nature. We simulated one point target with different SNR (SNR=17, SNR=25). The simulated image is reprocessed by the Capon algorithm. The profiles corresponding to the same range of the reprocessed images are plotted. The up-sampling factor is set as 16.

B. PSC selection criteria

The characteristics of Capon/APES reprocessed images are critical for PSC selection. We address two features related to PSC selection.

The first one is the adaptive resolution of Capon/APES reprocessed images. In Capon/APES based SAR reprocessing, a high up-sampling factor (in our case six to eight) is used to avoid missing highly-resolved targets [10]. This implies a varying degree of oversampling and correlation between samples. The adaptive nature is illustrated in Fig.1. We simulated one point-scatterer with different SNR (Signal to Noise Ratio) and reprocessed them with the Capon algorithm. The figure shows that the scatterer is resolved better (the mainlobe is much sharper) when the SNR is higher, and, furthermore, that the super-resolving factor is variable. Consequently, the resolution is typically much lower than the oversampling factor and the main-lobe of one scatterer may dominate a (variable) number of pixels. For classical PSC selection approaches, which assume a fixed resolution and critically sampled data, this would lead to the selection of pixel clusters rather than individual pixels as PSCs. On the other hand, the pixels whose amplitudes are local peaks are expected to have a higher SNR. Thus, for a specific point scatterer which dominates several pixels, only the pixel corresponding to the local amplitude-maximum should be selected as a PSC.

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0.20%	0.20%	0	0	0	0	0
0	0	0.10%	4.10%	10.60%	5.50%	0.20%	0	0	0
0	0	0.20%	11.70%	37.30%	10.80%	0.70%	0	0	0
0	0	0.10%	3.20%	11.80%	3%	0.20%	0	0	0
0	0	0	0	0	0.10%	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Fig. 2. Illustration of the peak jitter. We simulated 1000 SLC images with SNR=17 and reprocessed them with Capon algorithm. The peak position is calculated and the location occurrence rates are shown. The light-gray area corresponds to one grid cell of the original image. The dark-gray cell indicates the true position of the point scatterer.

The second feature is the peak jitter, which is illustrated in Fig.2. In the figure, the peaks are present in different positions with different probabilities. The effects of the peak jitter include two main aspects. First, it inspires the idea of applying the previously mentioned peak detection on the average amplitude image. The effect of the noise is canceled out when many images are averaged. Therefore, the peak positions on the average amplitude image are more accurate than on the individual image. Secondly, the positions of peaks corresponding to the same point scatterer may jitter a bit over time. We address this by introducing a peak matching step in order to produce a consistent amplitude time-series for any PSC pre-candidate. For a specific epoch, the position of the point scatterer can be matched by the closest peak within a distance. Subsequently, the normalized amplitude dispersion can be calculated for the individual *peaks*. The normalized amplitude dispersion can be used as a measurement of stability.

We also apply an amplitude threshold to filter out the spurious peaks caused by the noise.

Therefore, three criteria are used to select PSC from the refocused SAR images:

1. It is a local peak over surrounding pixels on the mean amplitude image:

$$\mu > \mu_i, i \in G, \quad (9)$$

where μ, μ_i are the mean amplitudes of the pixel of interest and the surrounding pixels, respectively, and G is the group of surrounding pixels.

2. The normalized amplitude dispersion of the corresponding peaks is below a threshold:

$$d = \frac{\sigma}{\mu} < d_0, \quad (10)$$

where d is the normalized amplitude dispersion, μ , σ are the mean and deviation of the amplitude and d_0 is the normalized amplitude dispersion threshold. The normalized amplitude dispersion can be calculated after peak matching.

3. The mean amplitude is above a noise threshold:

$$\mu > \mu_0. \quad (11)$$

The threshold is related to the statistics of the noise. The calculation method of the noise threshold is described in the next section.

III. SR-PSI PROCESSING

This section discusses the work-flow of SR-PSI. Compared to the traditional PSI, the main differences of SR-PSI are the super-resolution reprocessing and the PSC selection algorithm. Therefore, we focus on the process from the interferometric stack to PSC selection. we also discuss several SR reprocessing strategies and parameters setting methods.

A. SR-PSI Work-flow

The work-flow of SR-PSI is showed in Fig.3, including InSAR stack processing, SR reprocessing, PSC selection and other PSI processing. SR-PSI imports a stack of SLC images and exports a list of PSCs.

1. **InSAR stack processing.** This step imports a stack of SLC images and exports a stack of interferometric data. We apply traditional interferometric processing, including master image selection, spectral filtering, and coregistration.
2. **SR reprocessing.** This step imports the interferometric data stack and exports a stack of refocused SAR images. To implement the Capon/APES algorithms, the SAR images are brought from the space domain to the wavenumber domain by Discrete Fourier Transform (DFT). Furthermore, because both Capon and APES algorithms are memory-intensive, a chipping and mosaicking strategy is applied [9], [10]. This step includes spectral equalization, image chipping, 2-D DFT, Capon/APES processing, and chip-images mosaicking. Spectral equalization is applied in order to compensate the windowing that usually applied in the generation of SLC images. The equalizer is derived from the meta-data included with the SLC data. After the equalization, the power spectrum of the individual image is a 2-D rectangular function. Subsequently, the equalized images are divided into a set of chip images. 2-D DFT and Capon/APES are applied to the chip images. The refocused full SAR images are obtained after mosaicking the refocused chip images.

In the SR reprocessing, the size of chip images depends on the available computing resources. A 50% overlapping is recommended to avoid edge effects [10]. The impact of edge effects is illustrated by Fig.4. The region marked by the double-headed arrow is the edge of adjacent of the chip images. The error on the edge region without overlapping is much worse than the

Fig. 3. The workflow of SR-PSI. The workflow presents the super-resolution processing steps from the interferometric stack to PSC.

image with 50% overlapping, which illustrates the need for overlapping.

3. **PSC selection.** We obtain the mean amplitude by calculating the square root of the average intensity. The pixels whose amplitudes are local peaks are selected as initial PSCs. Peak matching is done to exploit the amplitudes of the initial PSCs over time. Considering that the interferometric stack is coregistered with sub-pixel precision, the maximum distance for peak matching is set as 0.5 original grid spacing. Subsequently, the normalized amplitude dispersion of each initial PSC can be calculated. We set the normalized dispersion threshold as 0.25 to guarantee the stability of phases for the scatterers [12].

The noise threshold is related to the statistics characteristic of an area with only noise. Let us assume that the noise in each channel is white Gaussian noise, having a normal distribution of

$$N(0, \sigma^2), \quad (12)$$

where σ is the standard deviation of the noise. Thus the

Fig. 4. Illustration of edge effects. We simulated a SAR image with 64 columns and 64 rows and employed Capon based SAR reprocessing algorithm. The size of the chip images is set as 32×32 . 0% overlapping and 50% overlapping are applied in SR reprocessing, separately. The SR reprocessed image without chipping-mosaicking strategy is the reference image. The corresponding profiles are plotted (The up-sampling factor is 8).

intensity of the individual images is a χ^2 distribution [20]. As predicted by the central limit theorem, the sum of the intensity is approaching a normal distribution, since usually more than 30 SAR images are involved in PSI. Hence the distribution of the sum of the intensity can be expressed as

$$N(2K\sigma^2, 4K\sigma^4), \quad (13)$$

where K indicates the quantity of individual images. With significance level set as 0.003, the intensity range of the noise is given by

$$N(2K\sigma^2 - 3\sqrt{4K}\sigma^2, 2K\sigma^2 + 3\sqrt{4K}\sigma^2). \quad (14)$$

Thus we set the noise threshold on the mean amplitude image as

$$\sqrt{\frac{2K\sigma^2 + 3\sqrt{4K}\sigma^2}{K}}. \quad (15)$$

The selected PSCs can be exported for further PSI processing, including atmospheric phase screen (APS) estimation and deformation estimation ([12], [14]).

B. SR reprocessing strategy

Since the direct implementation of Capon and APES estimators are computationally demanding, we use an efficient

algorithm in practice [21], [22]. A forward-backward averaging strategy are also applied to improve the performance [11].

As presented in (5), the sample covariance matrix is estimated from a finite number of snapshots. Thus the errors contained in the sample will cause inaccurate estimations of the covariance matrix. Joint processing or diagonal loading strategies can be used to improve the estimation. Joint Capon/APES processing is discussed in [10], [23]. Diagonal loading improves the condition number of the covariance matrix [24], [25], [26]. We apply diagonal loading in the following way:

$$\hat{R}_r = \hat{R} + \gamma I, \quad (16)$$

where $\hat{R}$ is the sample covariance matrix, γI is the diagonal loading level and γ is defined by

$$\gamma = \frac{\text{tr}(\hat{R})}{\text{SNR}_{dl} M_1 M_2}, \quad (17)$$

where $\text{tr}(\cdot)$ is the trace operator and SNR_{dl} is equivalent signal to noise ratio. For the experiments of TerraSAR-X data, we set γ as 17. Consequently, we consider 6 different algorithms:

- 1) Capon.
- 2) APES.
- 3) DL_Capon: Capon algorithm with diagonal loading.
- 4) DL_APES: APES algorithm with diagonal loading.
- 5) Joint_Capon: Capon algorithm with joint processing.
- 6) Joint_APES: APES algorithm with joint processing.

IV. NUMERICAL SIMULATION

A. Simulation Parameters

In order to evaluate the performance of SR-PSI under controlled conditions, a large quantity of time-series simulations has been done. We consider chip-images of 32×32 in range direction and azimuth direction, respectively. Each simulated stack consisted of 30 images corresponding to 30 epochs. Point scatterers are simulated in the images, with independent realizations of white circular-Gaussian noise added to each individual image. The phases of the individual scatterers are random variables uniformly distributed between $-\pi$ and π . Likewise, the amplitudes are assumed to be uniformly distributed between 1 and 100, making the biggest difference 40 dB. The interferometric phase is set as 0.

The simulations depend on two parameters:

1. Point Scatterer density: The adaptive nature of Capon/APES-based SAR processing implies that we should take different point scatterer densities into consideration. In our simulations, the number of point scatterers was varied between 10 and 610, which corresponds to point scatterer densities ranging from 0.0097 to 0.596 point scatterers per nominal-resolution cell.
2. SNR: White-circular Gaussian noise is added to the complex-valued data. For any given SNR, the variance of the noise can be expressed as

$$\sigma^2 = \frac{1}{2} \cdot \frac{\sum_{i=0}^{N-1} A_i^2}{N \cdot \text{SNR}} \quad (18)$$

where N indicates the number of point scatterers and A_i stands for the amplitude of individual scatterers. Thus

white-circular Gaussian noise with variance σ^2 is added to each simulated image. We set SNR as 10, 17, 20, respectively.

For each combination of parameters, 100 realizations were simulated. The results were averaged to compute the final statistics. In the implementation of traditional PSC algorithm, the images are oversampled by 2, followed by a calculation of the normalized amplitude dispersion. Only the local amplitude maxima are selected to filter out the sidelobes and sub-main lobes [13].

It is clear that the simulations represent an idealization of reality. For example, distributed scatterers are not included, and the clustering of point targets typically observed in real data is also ignored.

B. Benchmarking

Ideally, all point scatterers would yield the corresponding PSCs. Therefore, we use two main performance indicators to evaluate the performance of SR-PSI:

1. FRR (False Rejection Rate). This indicates the fraction of the point-scatterers that do not result in a corresponding PSC. The FRR is defined as

$$\text{FRR} = \frac{N_{\text{missing}}}{N_{\text{total}}}, \quad (19)$$

where N_{missing} is the number of the wrongly rejected pixels, N_{total} is the number of point scatterers.

2. FAR (False Acceptance Rate). This indicates the fraction of wrongly selected pixels with respect to the total number of selected PSCs:

$$\text{FAR} = \frac{N_{\text{false}}}{N_{\text{detected}}}. \quad (20)$$

To calculate FRR and FAR, we employed a point matching process after PSC selection. For each individual point in a set of PSCs, the nearest point in another set of PSCs is defined as its corresponding point. Since the resolved resolution of the SR reprocessed images depends on the nature of the scene, we need to evaluate the performance of SR-PSI under varied environments. We use point scatterer density and SNR as two main parameters to simulate different PSC sets and apply SR-PSI. Hence we can calculate FRR and FAR for each PSC set and obtain the statistics.

C. Simulation Results

Fig.5 and in Fig.6 show the FRR and FAR as a function of point-scatterer density for the three SNR values considered. Generally, both the FRR and the FAR increase as the point-scatterer density increases. The increase of false rejections happens because weaker targets are masked by stronger targets or their sidelobes. Falsely accepted targets are associated with sidelobes, as illustrated by the positive dependence of the FAR on the SNR for Fourier-based images, and to interfering sidelobes. For adaptive SR algorithms, the FAR is low for low scatterer densities even for the highest SNR case. This is because the ability of the SR methods used to strongly suppress sidelobes. Sidelobe suppression becomes more difficult

as the number of targets grows, which explains why the FAR increases with the scatterer density.

If we compare the performance of different PSC selection algorithms, Capon-related algorithms always perform better than APES-related algorithms and the traditional algorithm. When the point scatterer density is 0.2 and the SNR is 17, the FRR and FAR of the traditional algorithm is about 0.62 0.16, while Capon-related algorithms are around 0.47 0.04. In this case, the FRR and FAR are improved by 24% and 75%. The performance of APES-related algorithms is between both in most of the cases.

One question that may arise is if adaptive SR algorithms are phase-quality preserving. In order to explore this issue, we have characterized the phase error of the PSC selected by the different methods considered. For this analysis, we fixed the target-density at 0.2 targets per resolution cell and the SNR to 17 dB. Fig.7 shows the cumulative number of PSC for which the absolute value of the phase error is below a given value. The main finding is that high-quality PSC in Fourier-based images keep their phase high quality after SR processing.

V. EXPERIMENTAL RESULTS

In order to compare the performance with real-life data, we chose a test site around Rotterdam, the Netherlands. Fig. 8 shows the squared temporal mean of the intensity of a stack of 43 TerraSAR-X images over our test area, which was processed by the Delft Object-oriented Radar Interferometric Software (DORIS) [27]. These 43 images correspond to 43 epochs ranging from January 15, 2016, to May 22, 2018. The number of samples and lines of individual images is 768, respectively.

The images have been reprocessed by applying the different variants of the Capon and APES algorithms considered. Fig. 9 shows the number of PSCs obtained by each method. While all SR methods yield an increased amount of PSCs, the different flavors of Capon select significantly more PSCs than the diverse APES variants. The best results are obtained using single-epoch Capon without diagonal loading. In this case, 4112 PSCs are selected, which is a 58% increase with respect to the amount selected in the original, Fourier-based, data.

Similar results were obtained with a different stack of 32 TerraSAR-X SLC. In that case, the Capon-reprocessed stack yielded 56% more PSCs than the original stack. Fig.10 shows a detail of this stack, highlighting the sidelobe suppression performance of the different focusing approaches. In the figure, in panels (A), (C), and (F), the PSC in the white rectangle clearly correspond to azimuth sidelobes. The sidelobes are not selected as PSC anymore in Capon, Joint-Capon, APES and Joint-APES. Diagonal loading brings back some of these sidelobes. This can be expected since as the diagonal loading increases, both Capon and APES will tend to Fourier-based processing. Even though APES obtains a similar quantity of PSCs with the traditional algorithm, it selects fewer sidelobes (see Fig. 10 (A) (E)).

Having established that single-epoch Capon reprocessing seems to outperform all other SR approaches considered, we did a full PSI time-series analysis on Capon based SR

Fig. 5. FRR as a function of different point scatterer density for different PSC selection algorithms. SNR=10, 17, 20, respectively

Fig. 6. FAR as a function of different point scatterer density for different PSC selection algorithms. SNR=10, 17, 20, respectively.

Fig. 7. The cumulative number of PSC as a function of interferometric phase error for different PSC selection algorithms. The point density is set as 0.2 and the SNR is 17.

data using DePSI [16], obtaining the estimates of the linear deformation rate for all PSs. Like other PSI processing chains, DePSI does a classification and down-selection of PSs from the set of PSCs based on the interferometric consistency of the targets within the network solution. For this reason, in order to retain as many PSs as possible, the normalized dispersion threshold used to pre-select PSCs is usually relaxed to a relatively low value [16]. In our case study it was set to 0.45. For the final PS selection we use ensemble coherence as a quality estimator, setting the lower limit for selection at 0.8. With this criterion, we obtained 4515 PSs using the original data-stack, and 6708 PSs using the Capon-reprocessed stack. The number of PSs increase by approximately 50%.

Again, it is important to gain confidence in that the SR algorithms are preserving the quality of the phase. In principle this can be inferred from the previous paragraph, as PSI selection

is done on basis of the phase consistency. Nevertheless, in the following paragraphs we will examine the explicit outputs of the PSI processing. Our overall assumption is that the heights and deformation rates estimated using regular and PSI and SR-PSI should be consistent with each other. We start by one of the phase quality metrics calculated by DePSI, namely the standard deviation (STD) of the residuals between the deformation model and the deformation time series. The cumulative histogram of the STD is presented in Fig. 11. The ratio of number of PSs selected using the reprocessed stack and the original stack, respectively, is more or less constant for any standard-deviation threshold.

In order to validate that the deformations estimated using SR-PSI are consistent with those obtained using the standard approach, we focus now on the PSs selected in both cases. For the convenience of discussion, we refer to the PSs detected in both cases as common PSs. Likewise, with missing PSs we refer to PSs identified in the original stack that were not selected by the SR-PSI processing. Conversely, the newborn PSs are those only detected by the SR-PSI technique. We found 3812 common PSs, 703 missing PSs, and 2896 newborn PSs. We present the joint 2-D histogram of the deformation velocities and the joint 2-D histogram of the STD of common PSs, respectively. The performance comparison of common PSs is shown in the two subplots in Fig.12. In the upper subplot, most PS are concentrated along the reference line, which indicates that the deformation velocities of the common PS have a high similarity. This is further confirmed by their correlation coefficient, 0.98. The lower subplot presents the quality of common PSs, where the values also concentrate on the reference line. The mean STD of common PSs obtained from the original stack and from the Capon-reprocessed stack

Fig. 8. Squared mean intensity image of the original TerraSAR-X stack of the area of interest. The deformation velocities of the overall PSs are shown in Fig. 14. The region marked by the solid white line is analyzed in detail in Fig. 15 and the region marked by the dash line is shown in Fig. 16.

Fig. 9. The number of PSCs selected by different algorithms. The normalized amplitude dispersion threshold is set as 0.25.

are 1.27 mm and 1.29 mm, respectively. Both the STD plot and the mean STD indicate that the quality level is maintained in the super-resolution processing.

We now turn our attention to the estimated heights and deformation rates. Fig. 13 shows histograms of the retrieved height. The amount of PSs at any range of heights increases and the distributions are highly similar, which may indicate that the phase-qualities of the PSs are preserved after the Capon-based reprocessing.

To visually analyze the PSs, we show the deformation velocities of the PSs of the whole area in Fig. 14. We can observe similar deformation velocities for common PSs. The figure also shows the deformation of the missing PS and the newborn PS. Besides the increase of the PS density, we can also see that most newborn PSs are distributed in the urban area, which is consistent with the nature of PS. To visualize the details, We also show the deformation velocities of the PS in the region indicated by the solid white line in Fig. 8. Fig. 15 presents 213 common PS, from which we observe similar deformation. Obviously, the PSI density improvement implies that the number of newborn PS (335) is much larger than the

Fig. 10. Details of different algorithms: (A) Traditional (B) Capon (C) DL_Capon (D) Joint_Capon (E) APES (F) DL_APES (G) Joint_APES. The background is the squared mean intensity image of corresponding algorithms. The yellow marker represents PSC. The up-sampling factor of the images is 8.

Fig. 11. The cumulative histograms of the standard deviation (STD) for the PS selected by the traditional algorithm and obtained from the Capon-reprocessed stack.

number of missing ones (45). Aside from the increase of the number of PSs, it is interesting to examine their distribution. PSs tend to appear in clusters. While a large fraction of the newborn (and missing) PSs belong to these clusters, we also observe the emergence of new clusters, including some isolated points. In Fig. 16, we show the deformation velocities of PSs around a railway station. The region corresponds to the area denoted by the dash line in Fig. 8. The two lines of

PSs are mixed in the left subplot while we can recognize two lines of PSs clearly in the right subplot, which indicates that the resolution is improved.

VI. CONCLUSIONS

In this paper, we have studied the use of super-resolution methods based on spectral estimation techniques in PSI. The results of the simulations show that in terms of false-acceptance and false-rejection rates, SR-PSI outperforms standard PSI processing. Aside from the increased capability to discriminate between neighboring targets, which can lead to an improvement of the signal to clutter ratio, to a large extent, the increase of correctly selected PS candidates can be attributed to the improved suppression of sidelobes.

These findings are corroborated by the results obtained using a TerraSAR-X data-stack over the Rotterdam area, where the amount of selected PSC increased by 58% with respect to standard processing. Qualitatively, the results obtained showcase both the improved suppression of sidelobes and the improved ability to separate nearby targets. The amount of the final PS obtained from the full PSI processing increased by approximately 50%. Considering the results shown in, for example, [28], the PS density is roughly inversely proportional to the area of a resolution cell. Therefore, a roughly 50%

Fig. 12. The upper subplot indicates the joint 2-D histogram of the deformation velocities of the common PS. The lower subplot presents the joint 2-D histogram of the STD. The gray dashed line is the reference line with slope 1.0.

Fig. 13. The cumulative histograms of the heights for the PS selected by the traditional algorithm and obtained from the Capon-reprocessed stack.

increase in PS density would be equivalent to improving the resolution of the radar by a factor of approximately 0.66.

An interesting conclusion of our work is that the simplest variant of all the super-resolution algorithms considered, single-epoch based Capon-based processing without diagonal loading, provides the best results in the context of PSI. This is a somewhat different conclusion than what was reported in [10]. This is highly relevant because it implies the lowest computational effort and implementation complexity of all the methods considered. Nevertheless, it is worth pointing out that a lower level of diagonal loading, possibly determined based

on data statistics, could still yield better results.

From an algorithm development point of view, the main issue that this paper addresses is the selection of PSC in an adaptive processing scenario. The proposed approach based on peak-detection on the temporal average image, peak matching to deal with peak-position jitter, and a final selection based on the normalized amplitude dispersion, is straightforward and effective.

We have tested the proposed SR-PSI methodology within a full PSI processing chain. An important conclusion of this exercise is that the estimated deformation signal after the time series analysis is consistent with the results obtained with the classical approach. This confirms that the increase of selected PS does not go at the cost of their (phase) quality.

Future work should address several aspects. First, we would like to apply SR-PSI to SAR images generated by the different sensors and modes. In particular, we are interested in the application to Sentinel-1 time series acquired in TOPS mode([29], [30]).

It is clear that one big hurdle in the path towards making SR-PSI processing operational is the high computational costs associated to it. Strategies need to be investigated to optimally choose which portions of the image stacks should be processed using adaptive processing methods. Likewise, we need to identify promising approaches to deal with data with variable resolution.

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Fig. 14. The deformation velocities of common PSs, missing PSs and newborn PSs. Common PSs represents the PSs detected both in the original stack and in the SR-PSI processing. Missing PSs represents the PSs only selected from the original stack. Newborn PSs represents the PSs only selected from the Capon-reprocessed stack. The background of the left subplots and the right subplots show the squared mean intensity image of the original stack and the squared mean intensity image of the Capon-reprocessed stack, respectively. The oversampling factor is 8.

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Fig. 15. The deformation velocities of the PSs in the region indicated by the solid white line in Fig. 8.

Fig. 16. The deformation velocities of the PSs in the region indicated by the dash white line in Fig. 8. It corresponds to a tall building in real life.

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