

InSAR Phase Denoising

A review of current technologies and future directions

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Interferometric synthetic aperture radar (InSAR) is a powerful remote sensing tool that enhances information acquisition. During InSAR processing, the phase denoising of the interferogram is a mandatory step for topography mapping and deformation monitoring. During the past three decades, a large number of effective algorithms have been developed for efforts related to this topic. In this article, we give a comprehensive overview of InSAR phase-denoising methods, classifying the established and emerging algorithms into four main categories. The purpose is to provide the necessary guidelines and inspiration to related researchers by promoting the architecture development of InSAR signal processing.

PHASE-NOISE REDUCTION

As a modern, advanced sensor, InSAR [1]–[7] has been applied in remote sensing with great achievements and contributions. It plays an important role in topography mapping [1], deformation monitoring [3], and so forth [4]. Interferometry is considered one important feature of the current generation of remote sensors. A variety of air- and space-borne sensors have interferometric capability, such as F-SAR, the Shuttle Radar Topography Mission, COSMO-SkyMed TanDEM-X, and so on. Today, it is possible to provide standard, global digital elevation models with very high precision, one of the important missions of TanDEM-X [4].

The InSAR working principle is to measure the interferometric phase between two separate SAR images acquired from slightly different locations. Inevitably, interferometric phase noise [8] is introduced by inherent factors that can be roughly categorized as 1) system noise, such as thermal noise and SAR speckle noise; 2) decorrelation issues, including baseline, temporal, and volume decorrelation; and 3) inaccurate signal processing, mainly involving co-registration errors. In fact, all of these factors can be viewed as decorrelation issues because they



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introduce phase noise. It is well known that the phase-noise level is a spatial variant in the interferometric image domain, which is an inherent characteristic of InSAR system. The presence of noise increases the phase unwrapping difficulty and even leads to failures in the process, seriously degrading the final interferometric results [9], [10]. Therefore, phase-noise reduction is a necessary step during interferometric processing, and it has been developed as an important technology [11]–[20].

The original phase-noise reduction method can be traced to the multilook filter [11], which uses a simple moving average of the neighboring pixels in a rectangular window, that is, boxcar filtering [11]. Due to its easy implementation, the multilook filter has been employed during the digital elevation-model production of remote sensors, such as the *TanDEM-X*. The obvious disadvantages of the multilook filter include resolution loss and phase-fringe distortion when dealing with high-topography and high-heterogeneity areas. Essentially, the multilook filter assumes that the interferometric phase is locally stationary and that the scene reflectivity is homogeneous in a local window where the selected samples follow an independent and identical distribution (IID). In this case,

the multilook filter expects to perform a maximum-likelihood (ML) estimation [12], which is the foundation of most of the phase-filtering methods. However, this assumption is not always true due to topography variation and reflectivity heterogeneity, especially when facing region edges, man-made structures, and texture. In such situations, the interferometric phase tends to exhibit nonstationary and nonhomogeneous characteristics, conflicting with the IID assumption.

Simply put, the multilook filter is just a basic non-adaptive estimator, regardless of its interferometric-phase property.

Since the invention of InSAR technology, research on phase-noise reduction has been a hot topic. The objective of phase denoising is to accurately retrieve the interferometric phase while maintaining the spatial resolution. There are numerous established and emerging algorithms that show great potential. Among them, recently developed nonlocal (NL) filters exhibit unique superiorities that have attracted attention [21]. As opposed to traditional local filters, NL filters measure the patch similarity to select the most relevant samples and perform a weighted average on similar pixels to achieve noise reduction. The patch-wise sample-selection strategy is used instead of the pixel-wise method.

NL filters can capture phase redundancy using nonconnected pixels, breaking the local-filter restriction. The possible application of NL filters to the *TanDEM-X* is being studied; some attractive results can be found in [22]. Furthermore, new concepts in signal processing technologies, such as sparse signal processing and machine learning, have inspired innovative applications of InSAR phase denoising, such as sparse regularization [23] and singular-value decomposition (SVD) [24]. This group of methods has shown significant potential and can be treated as good candidates for a new generation of InSAR denoising processors.

To boost InSAR development, a review of phase denoising is necessary through an examination of current research. Although some of the literature has included a short review of the topic in their introductions, to the best of our knowledge there is still no comprehensive survey of phase-denoising technology. To fill the gap, this article attempts to provide an overview of existing methods and update the presentation of newly proposed techniques. A brief perspective on upcoming



methods is included to illustrate their potential, pointing out challenges and potential future directions.

INTERFEROMETRIC DATA MODEL

From the view of statistical signal processing, phase denoising is performed to retrieve the true value from noisy observations, such as an interferometric pair of SAR images. The statistical model of the interferometric data and the noise model of the interferometric phase constitute the basic foundation of InSAR technology. To describe the existing methods, it is necessary to introduce the signal model.

STATISTICAL MODEL

Let an interferometric pair of single-look complex SAR images be defined in a vector form as

$$\mathbf{k} = [z_1 \ z_2]^T, \quad (1)$$

where z_1 and z_2 are the obtained SAR images of two channels and T denotes the transpose operator. Usually, $\mathbf{k}$ can be assumed to follow a bivariate complex Gaussian distribution with zero means, and its probability-density function (PDF) is expressed as [25]

$$p(\mathbf{k}|\Sigma) = \frac{1}{\pi^2 \det(\Sigma)} \exp[-\mathbf{k}^H \Sigma^{-1} \mathbf{k}], \quad (2)$$

where H is the transpose and conjugate operator and Σ is a 2×2 covariance matrix of $\mathbf{k}$, which is given by

$$\Sigma = E(\mathbf{k}\mathbf{k}^H) = \begin{bmatrix} R_1 & \rho \cdot \sqrt{R_1 \cdot R_2} \\ \rho^* \cdot \sqrt{R_1 \cdot R_2} & R_2 \end{bmatrix}, \quad (3)$$

where $R_1 = E(|z_1|^2)$ and $R_2 = E(|z_2|^2)$ are the underlying reflectivities and ρ is the correlation coefficient between z_1 and z_2 , which can be further decomposed as [7], [26]

$$\begin{aligned} \rho &= \frac{E(z_1 \cdot z_2^*)}{\sqrt{E(|z_1|^2) \cdot E(|z_2|^2)}} = \frac{E(z_1 \cdot z_2^*)}{\sqrt{R_1 \cdot R_2}} = \gamma \cdot e^{j\phi_x} \\ \gamma &= |\rho| = \frac{|E(z_1 \cdot z_2^*)|}{\sqrt{R_1 \cdot R_2}} \in [0, 1], \end{aligned} \quad (4)$$

where γ is the so-called coherence with a real value and ϕ_x is the actual/noise-free interferometric phase. In (4), $I_z = z_1 \cdot z_2^*$ is defined as an interferogram by the conjugate multiplication between two SAR images.

From (2) and (3), the InSAR observations [that is, $a_1 = |z_1|$, $a_2 = |z_2|$, and $\phi_z = \angle(z_1 \cdot z_2^*)$, with $\angle(\cdot)$ a phase operator, $\phi_z \in (-\pi, \pi)$, and modulus 2π] can be statistically modeled under the constraint of $R = R_1 = R_2$, and the PDF is expressed as [27]

$$p(a_1, a_2, \phi_z | R, \gamma, \phi_x) = \frac{2a_1 a_2}{\pi R^2 (1 - \gamma^2)} \exp\left(-\frac{a_1^2 + a_2^2 - 2a_1 a_2 \beta}{R(1 - \gamma^2)}\right), \quad (5)$$

where $\beta = \gamma \cos(\phi_z - \phi_x)$. Then, the phase distribution can be obtained by integrating a_1 and a_2 out, which is expressed as [28]

$$p(\phi_z) = \frac{1 - \gamma^2}{2\pi} \cdot \left(\frac{\beta \left(\frac{1}{2}\pi + \arcsin(\beta) \right)}{(1 - \beta^2)^{3/2}} + \frac{1}{1 - \beta^2} \right). \quad (6)$$

The curve of $p(\phi_z - \phi_x)$ versus different values of coherence γ is plotted in Figure 1(a). As γ increases, the distribution of ϕ_z is much more compact, with a smaller noise turbulence, showing a higher quality for the interferometric phase. All of the noise sources mentioned earlier can be treated as decorrelation issues, reflecting the decrease in coherence. As a result, lower coherence means the presence of stronger noise, while higher coherence indicates a lower noise level. It is well known that the phase-noise level of the SAR interferogram is spatially variant, which is highly related to the reflectivity and tomography of the observed scenes. Figure 2(a) and (b) shows the interferometric phase and estimated coherence through shuttle-imaging radar-C/X-SAR data of Mount Etna [2], [13], used to illustrate this phenomenon.

With InSAR development, the distribution of the interferometric phase, ϕ_z , has been further investigated. Several

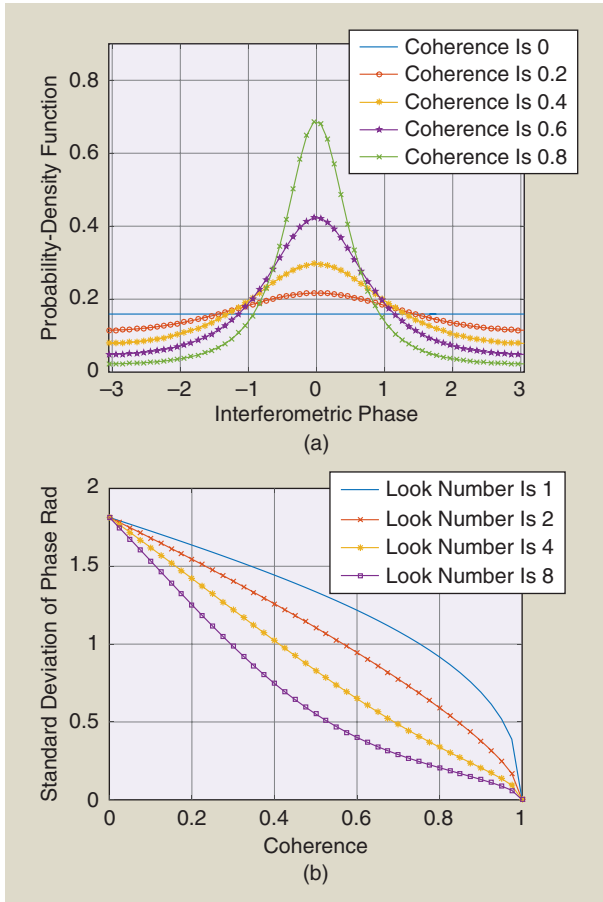


FIGURE 1. The statistics of the interferometric phase. (a) The probability-density function ($L = 1$). (b) The standard deviation of the noisy phase.

researchers have independently derived the PDF of the multilook interferometric phase, which is expressed as [11]

$$p^L(\phi_z) = \frac{\Gamma(L + \frac{1}{2})(1 - \gamma^2)^L \beta}{2\sqrt{\pi} \Gamma(L)(1 - \beta^2)^{L+1/2}} + \frac{(1 - \gamma^2)^L}{2\pi} F(L, 1; \frac{1}{2}; \beta^2), \quad (7)$$

where L is the look number, Γ is the gamma function, and F is the Gaussian hypergeometric function. By (6) and (7), the interferometric phase distribution is unimodal, symmetric, and modulus 2π , with its peak at the location of the actual interferometric phase, ϕ_x . By (7), the relationship of the phase noise between the coherence and look number is discovered; the curve of the phase's standard deviation with respect to coherence for specific look numbers is shown in Figure 1(b) [11]. The Cramer–Rao Bound of the standard deviation of the phase is also conducted as [11], [28]

$$\sigma_\phi = \frac{1}{\gamma} \frac{\sqrt{1 - \gamma^2}}{\sqrt{2L}}. \quad (8)$$

All of this evidence indicates that increasing the coherence, γ , and look number, L , is helpful to reduce the phase noise. For multilook filters, increasing the look number means expanding the window size to include more samples, assuming that all of the samples in the window are stationary and homogeneous to follow the IID. However, this assumption is not always true for scenes with a high topography and high heterogeneity. Therefore, the implementation of phase denoising needs to consider the InSAR phase characteristics.

PHASE-NOISE MODEL

In the real phase domain, the interferometric phase noise can be modeled as additive noise [13]:

$$\phi_z = \phi_x + v, \quad (9)$$

where v is the additive noise with a zero mean. In (9), ϕ_x and v are assumed to be independent of each other, which is an important characteristic for phase denoising. In this case, the standard deviation of the noise is denoted as $\sigma_v = \sigma_\phi$ and can be estimated from γ by using a look-up table, which is shown in Figure 1(b). As mentioned, v depends on the factors of the coherence, γ , and look number, L .

Due to the phase-warped property, ϕ_z is modulus 2π , and phase unwrapping is a necessary step for noise reduction in the real phase domain. Alternatively, phase denoising using complex data is more effective and powerful. The noisy phase in the complex domain is modeled as [29]

$$S_z = S_x + n_v, \quad (10)$$

where $S_z = e^{j\phi_z}$, $S_x = N_c \cdot e^{j\phi_x}$, and n_v are the measured phase, noise-free phase, and phase noise in the complex domain, respectively. In (10), $N_c = (\pi/4) \cdot \gamma \cdot F((1/2), (1/2); 2; \gamma^2)$ is determined by coherence γ , which can also be used to indicate phase quality. The real and imaginary parts of n_v are treated

as zero-mean additive noise, which can be modeled as independent from the actual phase, ϕ_x . In a similar way, n_v also depends on the terms of coherence γ and look number L .

Finally, phase denoising can also be realized from interferogram estimation/filtering, together with despeckling processing. As a foundation of interferogram denoising, the signal model of interferogram I_z is given by [21]

$$I_z = I_x + n_l, \quad I_x = \sqrt{R_1 \cdot R_2} \cdot \gamma \cdot e^{j\phi_x}, \quad (11)$$

where I_x is the noise-free interferogram and n_l is the signal-dependent noise (the dependence arises from the speckle-noise model, which is not a focus of this article). Under the constraint of $R = R_1 = R_2$, I_x reduces to $I_x = R \cdot \gamma \cdot e^{j\phi_x}$, while the corresponding likelihood function is denoted as (6).

Based on the aforementioned interferometric-data model, a variety of InSAR phase-denoising methods have been proposed in the literature. According to the history of their algorithm development and technology features, InSAR phase-denoising methods can be categorized as traditional local spatial-domain filters, transformed-domain filters, NL filters, and filters based on newly advanced methods. The first two represent the groups of traditional and mature methods in this field. Figure 3 presents statistics for journal and conference publications covering them. It can be seen

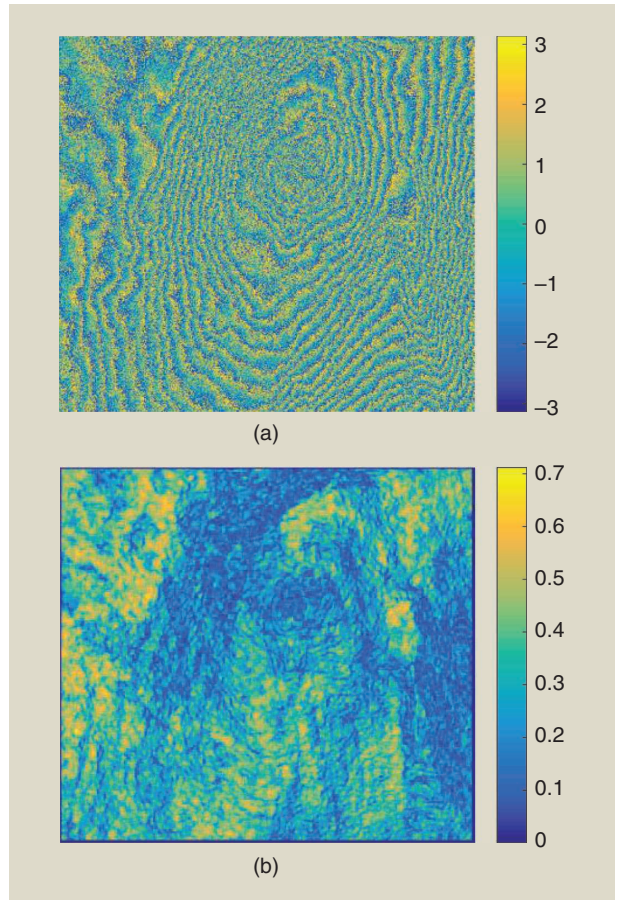


FIGURE 2. The real interferometric data of Mount Etna. (a) The noisy interferometric phase. (b) The coherence of (a).

that there has been no significant growth in the number of publications since 2002, indicating the relatively mature status of the research. The NL filter can be treated as a new generation of phase-denoising technology. Figure 4 displays the publication statistics for NL filters and shows that there has been significant research growth since 2009. Considering one typical advanced technique, publication statistics for

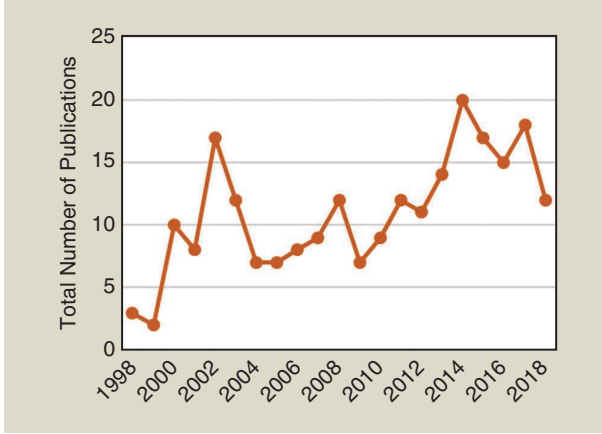


FIGURE 3. The number of publications concerning local- and transformed-domain filters.

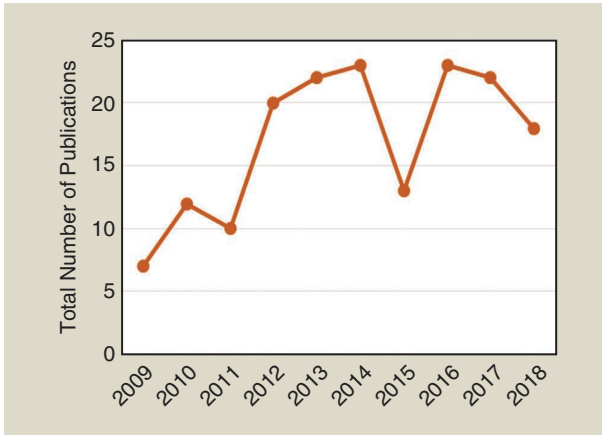


FIGURE 4. The number of publications covering NL filters.

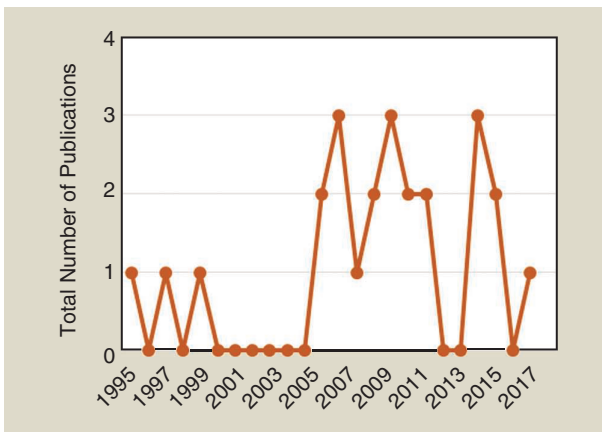


FIGURE 5. The number of publications about sparse methods.

sparse methods are given in Figure 5. As a very new technology, the sparse techniques methods have had limited study and need more attention to evaluate their potential. In the following, a nonexhaustive review is attempted to classify the existing methods, analyzing the strengths and limitations of different technologies.

REVIEW OF LOCAL FILTERS

As a mature research field, local-filter methods have a long history, and the multilook filter [11], [30]–[32] can be treated as one of the very earliest. The basic principle of these methods employs a local window with pixels connected to select stationary and homogenous samples for phase estimation. In this section, the introduction of local filters is divided into four groups. For clarity, a processing flowchart is shown in Figure 6.

MEDIAN/MEAN FILTERS

These methods utilize the mathematical morphologies of mean [19], [33]–[36] and median [16]–[18], [37]–[39] functions to estimate the phase, assuming that the local phase in a small window is statistically stationary and homogenous so that it follows the IID assumption. The purpose of a pivoting mean/median filter is to obtain optimal filtered results from local statistics. The formulation of the pivoting mean filter is expressed as

$$\tilde{\phi}_x^{\text{mean}}(k, l) = \text{mean}_{(k', l') \in \text{win}(k, l)} \left(\angle \left(\frac{S_z(k', l')}{d_{k, l}} \right) \right) + \angle(d_{k, l})$$

$$d_{k, l} = \sum_{(k', l') \in \text{win}(k, l)} S_z(k', l'), \quad (12)$$

where $\text{win}(k, l)$ is a filter window centered at site (k, l) , $\tilde{\phi}_x^{\text{mean}}(k, l)$ is the estimated phase of pixel (k, l) , and $\text{mean}(\cdot)$ is an average operator. Meanwhile, the formulation of the median filter is given by

$$\tilde{\phi}_x^{\text{median}}(k, l) = \text{median}_{(k', l') \in \text{win}(k, l)} \left(\angle \left(\frac{S_z(k', l')}{d_{k, l}} \right) \right) + \angle(d_{k, l}), \quad (13)$$

where $\text{median}(\cdot)$ is a median operator. The preconditions for both filters depend significantly on the local phase's stationary and homogenous property: the topography fluctuation in the local region is slow for the sampling rate, and the adjacent pixels have a high correlation. When the noise is additive Gaussian noise, the pivoting mean filter is statistically optimal from the view of ML estimation. However, the stationary and homogenous assumption conflicts with fast topography variations. Similar to the multilook filter, the mean filter has an oversmoothing effect and cannot deal well with the phase details of rapid topography variations. Compared with the mean filter, the pivoting median form has a better preservation of the phase fringe, but the power of its noise suppression reduces to some degree. Besides, one major limitation is that this group of methods is nonadaptive, regardless of

the local spatial variation of the selected samples (such as noise level) using an equal average. Several modifications have been designed to gain improvements by distinguishing the contributions among different samples, such as the weighted average [36], [39].

LEE FILTER AND ITS REFINED FORMS

These methods use a locally directional window and apply a Lee filter [13] or as refined version [14], [40], [41] with adaptive local noise adjustment. Lee-filter processing can be divided into two steps. The first is stationary and homogenous sample selection by evaluating candidates from different directional windows. To adaptively capture the phase fringe, the Lee filter has predesigned windows with 16 directions and tries to choose the best one. The next step involves statistical parameter estimation and minimum mean-square error estimation. The generalized mathematical formulation of the Lee filter is shown as

$$\begin{aligned} \tilde{\phi}_x &= \tilde{\phi}_z + \eta \cdot (\phi_z - \tilde{\phi}_z) \\ \eta &= \frac{\text{var}(\phi_x)}{\text{var}(\phi_z)} = \frac{\text{var}(\phi_z) - \sigma_v^2}{\text{var}(\phi_z)}, \end{aligned} \quad (14)$$

where $\tilde{\phi}_x$ is the estimation of ϕ_x , $\tilde{\phi}_z$ is the mean value of ϕ_z in the filtering window, $\eta \in [0, 1]$ is a weighted coefficient of the Lee filter, and, as mentioned, σ_v can be estimated from γ using a look-up table. To calculate $\tilde{\phi}_z$ and $\text{var}(\phi_z)$, ϕ_z needs to be unwrapped in the filtering window. As an alternative, the complex formulation of the Lee filter is given by

$$\tilde{S}_x = \tilde{S}_z + \eta \cdot (S_z - \tilde{S}_z), \quad (15)$$

where $\tilde{S}_x = e^{j\tilde{\phi}_x}$, $S_z = e^{j\phi_z}$, and $\tilde{S}_z$ is the normalized mean value of S_z in the filtering window. In areas of high coherence, the value of η is very close to one, and the Lee filter simplifies to $\tilde{\phi}_x \approx \phi_x$, avoiding the smoothing effect. In low-coherence areas, the Lee filter reduces to a mean filter as $\tilde{\phi}_x \approx \tilde{\phi}_z$ when $\eta = 0$. The performance of the Lee filter greatly depends on the accuracy of the directional window selection and parameter estimation. The major drawbacks of the Lee filter concern the restricted number of predefined windows and sensitivity to strong noise, which is limited against the phase fringe for complicated structures and textures. The Lee filter does not work well in high-topography areas and tends to introduce undesired artifacts, such as discontinuity. Several modifications have been designed, such as the

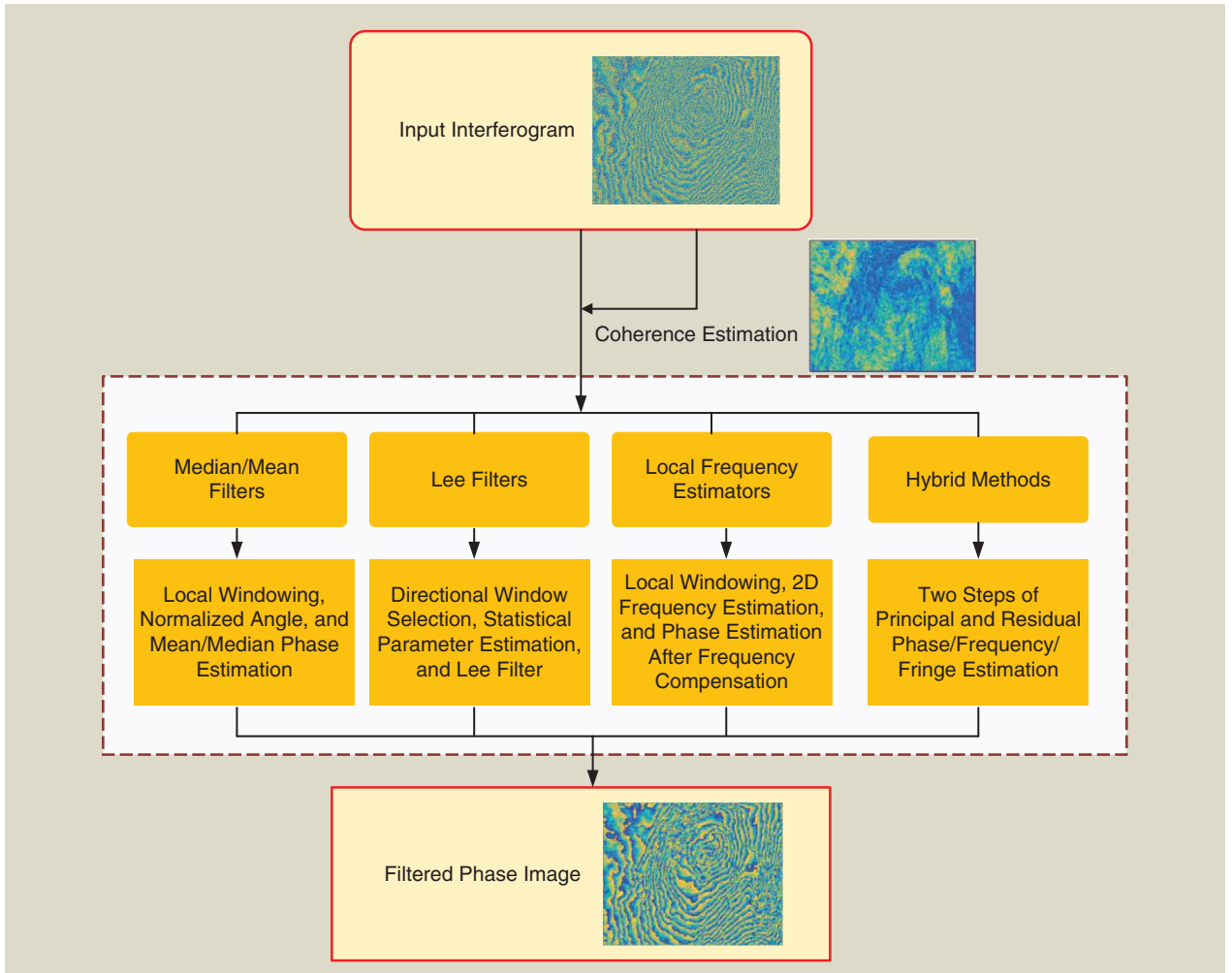


FIGURE 6. A processing flowchart for local filters.

local adaptive filter [15], [40] and refined Lee filter [14]. To overcome the window-number constraint, the directional window is adaptively estimated by retrieving the local frequency to determine the direction of the phase fringe [15]. The refined Lee filter proposed in [14] has modifications to improve the robustness of the directional window selection and statistical parameter estimation.

LOCAL-FREQUENCY ESTIMATORS

Local-frequency estimators are based on polynomial-phase models, such as linear [42]–[45] and nonlinear [46]–[49]. These methods estimate the local frequency of the interferometric phase to derive the phase fringe. Usually, the local phase in a small window is modeled as a sine wave with one major component, which is shown as

$$S_z^{\text{win}}(k, l) \approx a_{k,l} \cdot \exp[j2\pi(k \cdot f_x + l \cdot f_y)] + n_v(k, l), \quad (16)$$

where $S_z^{\text{win}}(k, l)$ is a local-window form of $S_z(k, l)$ centered at site (k, l) , and $a_{k,l}$ and (f_x, f_y) are the coefficient and 2D frequency, respectively. Then, (f_x, f_y) can be approximated using spectrum estimators, such as ML [42], vector covariance matrix [42], and multiple-signal classification [45]. Based on the approximated fringe frequencies, the filtered phase can be estimated as

$$\tilde{\phi}_x(k, l) = \angle \left(\sum_k \sum_l S_z^{\text{win}}(k, l) \cdot \exp[-j2\pi(k \cdot \tilde{f}_x + l \cdot \tilde{f}_y)] \right), \quad (17)$$

where $(\tilde{f}_x, \tilde{f}_y)$ is the estimated 2D frequency. In practice, the linear-frequency model is not adequately accurate because it neglects other frequency components. To overcome this limitation, several innovative strategies, such as achieving iteration by varying the window size [18] and using nonlinear-phase modeling [47]–[49], are applied to preserve the phase details of the fringe and texture. The order of the selected model is crucial to this group of methods. The higher the chosen order, the more accurate the phase estimation becomes. However, there is a cost in terms of increased computational load. As a result, there must be a balance between the order selection and computational complexity. Integration methods including phase-frequency estimation and unwrapping have been studied [51]–[57], but they are not discussed here.

HYBRID METHODS

The procedure for these methods is usually decomposed into two-step estimations. The basic idea is that the interferometric phase can be separated into principal and residual components, such as a low-resolution fringe and high-resolution pattern [18], [41], [60], [61]. The principal component can usually be extracted using the local-frequency estimation technique and so on. After the principal phase compensation, the interferometric phase's residual component can be estimated more precisely. It is

obvious that the phase is estimated in a hybrid manner, which is shown as

$$\tilde{\phi}_x = \tilde{\phi}_x^{\text{LR}} + \tilde{\phi}_x^{\text{HR}}, \quad (18)$$

where $\tilde{\phi}_x^{\text{LR}}$ and $\tilde{\phi}_x^{\text{HR}}$ are the estimations of the principal and residual phases, respectively. For the local filters, the sample-selection strategy, such as the window form, is critical to the phase/frequency estimation. The developed window can be roughly classified as an oriented/directional window [13]–[15], an adaptive size-varying window [18], [43], and a region-growing mask [59], [60]. The region-growing (also known as the *intensity-driven adaptive neighborhood*) method [60] employs a local window with an adaptive shape and size to search for similar pixels that are stationary and homogenous. Among traditional local filters, the region-growing method can select the most relevant high-quality samples, establishing it as one of best of the sample selectors.

COMPARISON OF LOCAL FILTERS

In this section, numerical experiments using the aforementioned interferometric data are performed to compare typical local filters, including the pivoting mean filter [19], pivoting median filter [39], Lee filter [13], ML method [42], and region-growing method [60]. Figure 7 presents the filtered images; the rows display the filtered phase, phase difference (between filtered and noisy examples), residue, and coherence, respectively. It can be seen that the pivoting mean and median filters tend to introduce phase discontinuity in the highly sloped areas, producing many residues. The ML method has a better performance in the high-topography regions. However, it produces excessive filtering, which leads to a loss of phase details. In addition, the size of the filter window greatly affects the ML results. The Lee filter performs better for noise reduction and detail preservation. However, it introduces artifacts in the areas of very low coherence. Among the filters, the region-growing method's performance is the best, although its phase estimation in highly sloped regions is quite limited. We can conclude that traditional local filters are not very effective for dealing with high topography variations, which is an inherent limitation.

REVIEW OF TRANSFORMED-DOMAIN FILTERS

Instead of filtering in the spatial domain, InSAR phase denoising can be performed in the transformed domain. Transformed-domain filters possess the superior quality of enhancing the phase signatures to be more separable from the noise. In this section, we introduce transformed-domain filters and divide them into two groups. For clarity, their processing flowchart appears as Figure 8.

FREQUENCY-DOMAIN METHODS

Frequency domain usually refers to the Fourier transform and discrete cosine transform. The most typical and effective of these denoising techniques is the Goldstein filter [62] and

its refined versions [63]–[74]. The basic idea ties into the fact that the interferometric phase is locally stationary and homogeneous, and most of the useful components of the local phase are typically limited to a narrow band, while the noise is distributed through the entire frequency band. The Goldstein filter transfers the interferometric phase image into the frequency domain and weights the phase spectrum for noise reduction. The generalized formulation of the Goldstein filter is expressed as

$$\tilde{S}_x(k, l) = \text{IFFT2}(\text{SM}(|Y_z^{\text{win}}(p, q)|)^\alpha \cdot Y_z^{\text{win}}(p, q)), \quad (19)$$

where Y_z^{win} is the Fourier spectrum of the interferometric-phase image in a local window centered at site (k, l) , $\text{IFFT2}(\cdot)$ is the 2D inverse Fourier transform, $\text{SM}(\cdot)$ represents the smoothing operation, and α is the filtered parameter. The proper selection of α is very important. The Goldstein filter's performance is significantly affected by the patch size of the local window and filter parameter α .

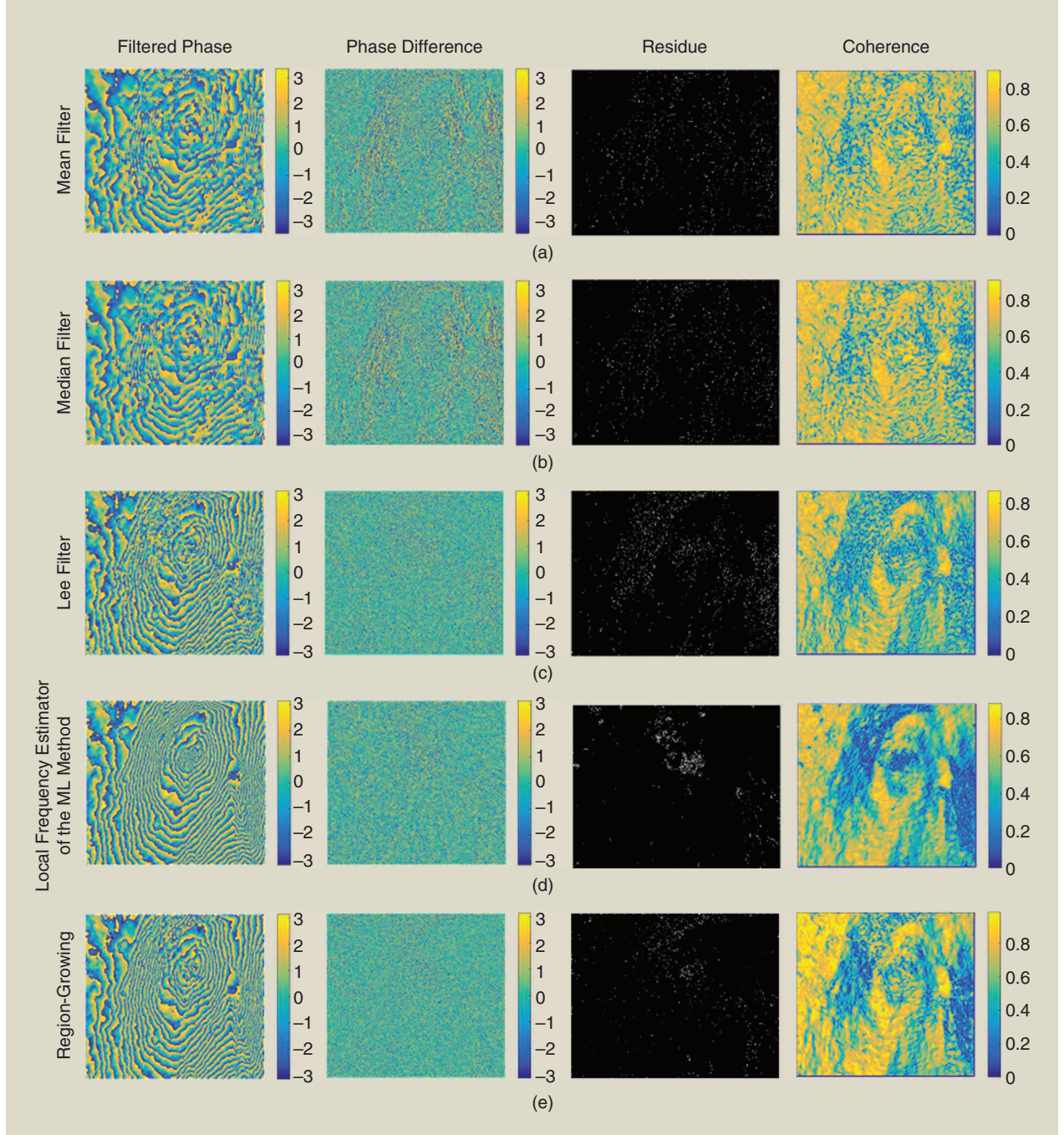


FIGURE 7. The filtered phase images obtained using local filters. (a) The pivoting mean filter [19] (residue number: 2,831). (b) The pivoting median filter [39] (residue number: 2,826). (c) The Lee filter [13] (residue number: 6,161). (d) The local frequency estimator derived through the ML method [42] (residue number: 2,409). (e) The region-growing method [60] (residue number: 2,189).

When $\alpha=0$, there is no filter power and processing. When $\alpha=1$, the filtering power is at its strongest. Baran [63] has defined the filtering parameter as $\alpha=1-\gamma$, meaning that the coherence reflects the noise level to adaptively control the filtering strength. Several improvements have been achieved by providing a more moderate estimation of the filtering parameter [67], adaptive window size [65], topography compensation [64], and so forth [70]–[74].

WAVELET-DOMAIN FILTERS

The wavelet transform can enhance interferometric-phase signatures using multiresolution representation. The multiresolution property has the advantages of reliable noise separation and perfect nonstationary signal analysis. Lopez and Fabregas propose to apply the wavelet transform for phase denoising by modeling the phase noise in the wavelet domain [29], which provides a foundation for this group of methods. Based on the assumption of a linear wavelet transform, the additive phase-noise model in (10) can easily be generated to the wavelet domain. The wavelet transform of (10) can be expressed as

$$W_z = W_x + W_v, \quad (20)$$

where W_z , W_x , and W_v are the wavelet transforms of S_z , S_x , and n_v , respectively. In the i th scale of the 2D wavelet transform, the detailed form of W_x is given by

$$W_x(k, l, i) = N_c \cdot 2^i e^{j\phi_x^w(k, l, i)}, \quad (21)$$

where $\phi_x^w(k, l, i)$ represents the phase information at site (k, l) of i th wavelet scale. In terms of noise, the variance is unchanged before and after the wavelet transform. When one deep scale is applied, the wavelet transform multiplies the phase term by a factor of two without altering the noise level [29]. The behavior of the wavelet transform can effectively locate, preserve, and amplify the actual phase in the wavelet domain. In this way, the phase and noise can be more easily separated. The phase-noise reduction is performed by means of the appropriate nonlinear processing,

such as wavelet shrinkage and filtering, which can be expressed in a generalized formulation as

$$\tilde{W}_x = H(W_z) \cdot W_z, \quad (22)$$

where $H(\cdot)$ denotes a shrinkage or filter function. The inverse wavelet transform is applied to $\tilde{W}_x$, and the phase image can be obtained with noise reduction. The performance of the wavelet filter depends on the scale of the wavelet decomposition and the shrinkage/filter function used in the wavelet domain. For better multiresolution capability, the undecimated wavelet transform [76] and wavelet packets [77], [78] are used to improve phase-denoising performance. It is commonly accepted that wavelet-transformed filters preserve the spatial resolution well due to their perfect representation of nonstationary signals from multiresolution properties.

COMPARISON OF TRANSFORMED-DOMAIN FILTERS

In this section, experiments using the same dataset are carried out to demonstrate the performance of transformed-domain filters. Figure 9 shows the results of the Goldstein and wavelet filters (their residue numbers are 18,620 and 25,289), respectively. For the Goldstein filter [62], the parameter is set as $\alpha=0.999$, with a strong filtering effect. The Goldstein filter has a good phase-denoising performance in the high-coherence areas. However, there are many residues and large phase differences in the low-coherence areas, indicating phase distortion in the high-topography areas. For the wavelet filter [29], the dual-tree complex wavelet transform is used for excellent phase preservation. It can be seen from Figure 9 that, in comparison with the Goldstein filter, the wavelet filter performs better for phase-detail preservation because the wavelet coefficients of the noise remain, amplifying only the signal components.

REVIEW OF NONLOCAL FILTERS

NL filters have been successfully deployed in InSAR phase denoising and become a frequent research topic. They measure patch similarity without restricting the search window

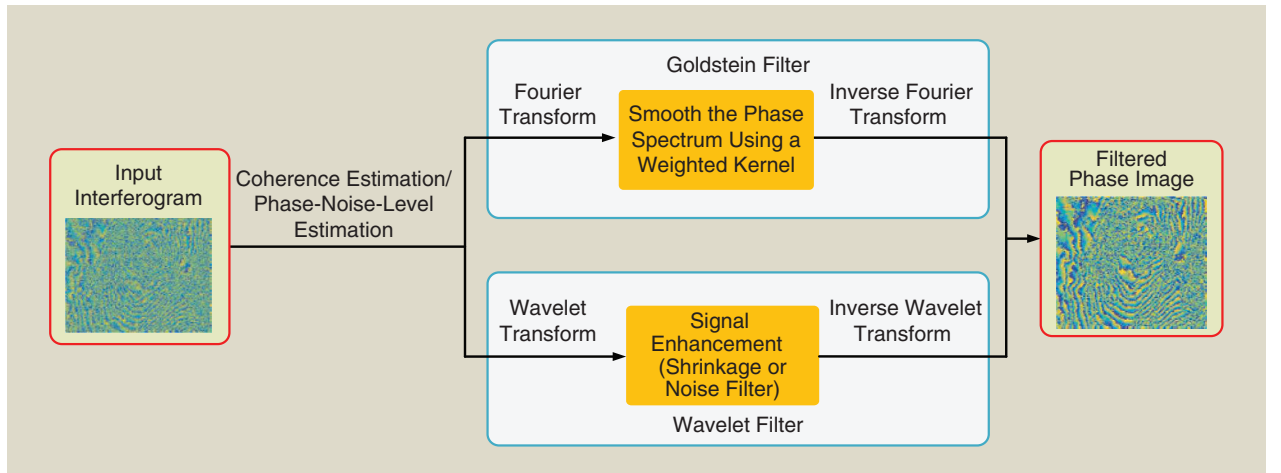


FIGURE 8. A processing flowchart for transformed-domain filters.

in a local region, overcoming the neighbor-connection limitation. The NL-filter concept can be traced to Lee's pioneering work [79]; Buades's seminal contributions [80], [81] developed the patch-based filter framework. NL filters were incorporated into InSAR by establishing a new technology known as *NL-InSAR* [21], which is one of the most typical and effective phase-denoising methods. NL filters employ the patch-wise method to measure the patch similarity in the interferogram domain, and the weighted average is applied to estimate the filtered interferogram and phase denoising. With this framework, the most relevant samples can be reliably selected, and phase denoising is achieved by distinguishing the contributions among different samples. NL filters have the advantage of preserving the phase fringe/texture by effectively capturing the phase structure and extracting the phase redundancy in the patch space. Compared with traditional local filters, NL filters are more powerful and possess unique superiorities, such as better

performance in dealing with high topographies and heterogeneities (such as isolated scenes). For clarity, the NL-filter processing flowchart is presented as Figure 10.

CONCEPT OF NONLOCAL FILTERS

Buades [80], [81] established the NL-filter framework through the patch-based method and weighted-average strategy. To estimate the noise-free interferogram at site u , the generalized formulation of the NL filter is expressed as

$$\tilde{I}_x^u = \frac{\sum_t \omega_{u,t} \cdot I_z^t}{\sum_t \omega_{u,t}}, \quad \omega_u = \sum_t \omega_{u,t} \quad (23)$$

where $\omega_{u,t}$ is the weighted coefficient derived by considering the contribution from the pixel at site t . The key idea behind the NL filter is that the weight, $\omega_{u,t}$, is measured from the similarity between patches $\mathbb{C}_u$ (centered at site u)

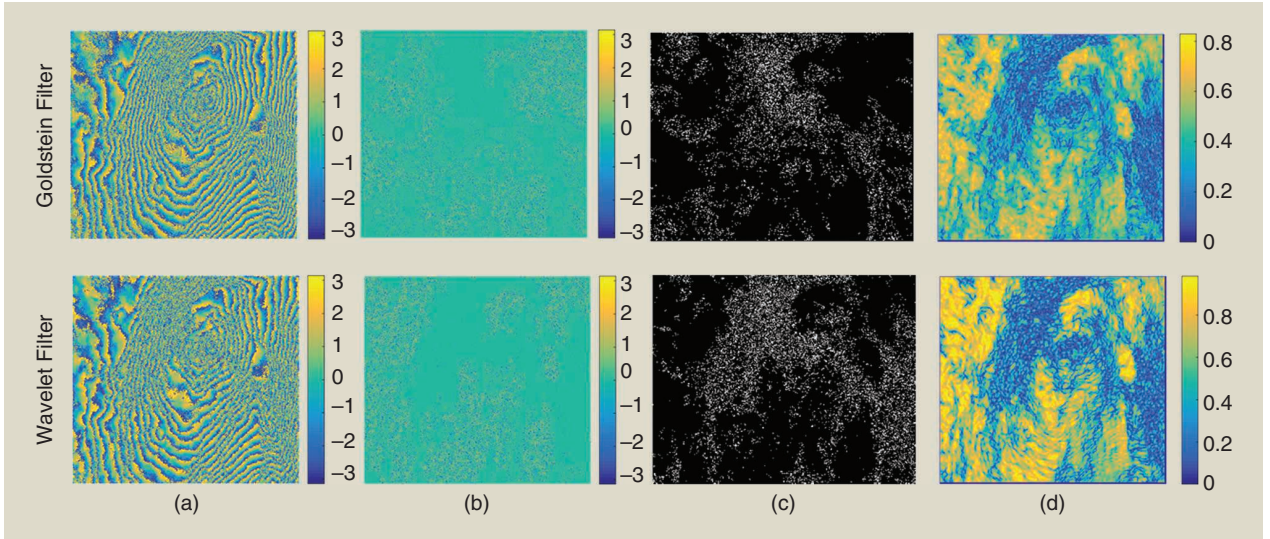


FIGURE 9. The filtered phase images obtained using transformed-domain filters. The (a) filtered phase, (b) phase difference, (c) residues, and (d) coherence of the filtered images. The first and second rows show the Goldstein [62] and wavelet filters [29], respectively.

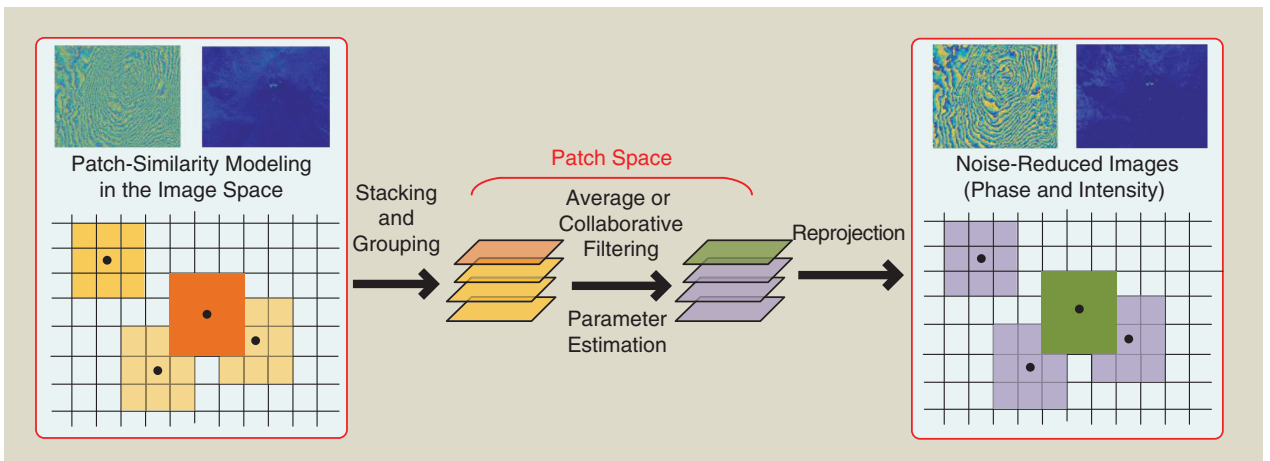


FIGURE 10. A processing flowchart for NL filters.

and $\mathbb{C}_t$ (centered at site t), which is known as the *patch-based method*. Usually, $\omega_{u,t}$ is designed using an exponential kernel of the patch-similarity parameter, Δ , as

$$\omega_{u,t} = \exp\left[\frac{\Delta}{h}\right], \quad (24)$$

where a large value of Δ means a stronger patch similarity to produce a large weight, $\omega_{u,t}$, and h controls the decay of the exponential function. Essentially, the choice of h is a tradeoff between filtering strength and detail preservation. From (24), choosing a large value for h leads to a less discriminative weight and stronger filtering strength, while a smaller value enhances patch dissimilarity for better detail preservation.

The design of the weights, $\omega_{u,t}$, is an important NL-filter issue that is associated with patch similarity. Properly modeling the similarity criteria for NL filters in InSAR is crucial to the phase-denoising performance. The transformed-domain filter is also helpful for phase denoising. Combining the NL principle with a transformed-domain filter, such as wavelet transform, is an interesting approach. The review of NL filters is divided into two main groups in this section.

PROBABILISTIC PATCH-BASED FILTERS

The probabilistic patch-based (PPB) filter [21] extends the NL filter to SAR/InSAR applications using the weighted maximum-likelihood estimator [81]. Based on the statistical model of the interferometric data in (5), the generalized formulation of the PPB filter for interferogram denoising is shown as [21]

$$\tilde{\Theta}_u = \arg\max_{\Theta_u} \sum_t \omega_{u,t} \cdot \log p(\mathbf{O}_t | \Theta_u), \quad (25)$$

where $\Theta_u = (R_u, \gamma_u, \phi_x^u)$ is a set of desired parameters for the pixel at site u and $\mathbf{O}_t = (a_1^t, a_2^t, \phi_z^t)$ denotes the observations of the pixel at site t . The detailed form of the InSAR-parameters estimation is given by

$$\begin{aligned} \tilde{\phi}_x^u &= \angle \tilde{I}_x^u, \quad \tilde{\gamma}_u = \frac{|\tilde{I}_x^u|}{\tilde{R}_u} \\ \tilde{R}_u &= \sum_t \frac{\omega_{u,t}}{\omega_u} \cdot \frac{|z_1^t|^2 + |z_2^t|^2}{2}. \end{aligned} \quad (26)$$

For the PPB filter in [21], the patch similarity measures how likely patches $\mathbb{C}_u$ and $\mathbb{C}_t$ are to follow the same distribution. Based on the independence assumption of the pixels in each patch, the patch similarity can be computed pixel-wise. The weight, $\omega_{u,t}$, is defined as [21]

$$\begin{aligned} \omega_{u,t} &\stackrel{\Delta}{=} p(\mathbf{O}_{\mathbb{C}_u} | \mathbf{O}_{\mathbb{C}_t} | \Theta_{\mathbb{C}_u} = \Theta_{\mathbb{C}_t})^{1/h} \\ &= \prod_m p(\mathbf{O}_{\mathbb{C}_u(m)}, \mathbf{O}_{\mathbb{C}_t(m)} | \Theta_{\mathbb{C}_u(m)} = \Theta_{\mathbb{C}_t(m)})^{1/h}, \end{aligned} \quad (27)$$

where $\mathbb{C}_u(m)/\mathbb{C}_t(m)$ is the m th pixel of patch $\mathbb{C}_u/\mathbb{C}_t$. Accordingly, this means that the similarity parameter, Δ , is computed as [21]

$$\Delta_{u,t}^1 = \sum_m \log p(\mathbf{O}_{\mathbb{C}_u(m)}, \mathbf{O}_{\mathbb{C}_t(m)} | \Theta_{\mathbb{C}_u(m)} = \Theta_{\mathbb{C}_t(m)}). \quad (28)$$

It is important that the PPB filter employs an iterative-manner strategy. Using the intermediate results, the estimation accuracy of the weight computation can be enhanced using a posterior probability as

$$p(\Theta_{\mathbb{C}_u} = \Theta_{\mathbb{C}_t} | \mathbf{O}) \propto p(\mathbf{O}_{\mathbb{C}_u}, \mathbf{O}_{\mathbb{C}_t} | \Theta_{\mathbb{C}_u} = \Theta_{\mathbb{C}_t}) \cdot p(\Theta_{\mathbb{C}_u} = \Theta_{\mathbb{C}_t}), \quad (29)$$

where $p(\Theta_{\mathbb{C}_u} = \Theta_{\mathbb{C}_t})$ is a prior term. The similarity parameter, Δ , is refined as [21]

$$\Delta_{u,t}^2 = \sum_m \log p(\Theta_{\mathbb{C}_u(m)} = \Theta_{\mathbb{C}_t(m)} | \mathbf{O}). \quad (30)$$

In this way, the weights can be refined at each iteration. The performance of the PPB filter relies on the accuracy of the parameter estimation, that is, $\Theta_{\mathbb{C}_u(m)}$ and $\Theta_{\mathbb{C}_t(m)}$. The presence of phase topography and scene heterogeneity conflicts with the collection of relevant samples. In this case, the PPB filter may produce oversmoothing in areas of high topography and high heterogeneity. Several modifications [22], [82]–[84], such as topography compensation and heterogeneity measurement, have been designed to improve the reliability of the PPB filter in interferogram denoising. Due to the iterative manner of the PPB approach, the NL filter has been studied to consider its practical application on a graphics-processing-unit platform [85].

BLOCK-MATCHING 3D FILTERS

The InSAR block-matching 3D (BM3D) filter [86] modifies the traditional BM3D filter for application in the InSAR domain. The concept of the InSAR BM3D filter can be decomposed into three main steps:

- 1) use the patch-based method to collect similar patches and group/stack them
- 2) use the wavelet transform on the 3D block data, phase filtering in the wavelet domain, and inverse wavelet transform to move the data back to the patch domain
- 3) return all of the filtered patches to their original locations and aggregate them through overlapped data fusion.

The basic principle of noise reduction lies in the fact that the 3D wavelet transform can enhance the interferometric-phase signatures, providing more reliable noise separation. The formulation of the 3D wavelet transform on patch-block data is expressed as

$$W_{I_z} = W_{I_x} + W_{n_I}. \quad (31)$$

The phase-noise reduction in the wavelet domain is decomposed into two steps, where the first is the hard thresholding, formulated as

$$\tilde{W}_{I_x}^u = \begin{cases} W_{I_x}^u & |W_{I_x}^u| \\ 0 & \text{otherwise} \end{cases} \quad (32)$$

where $W_{I_z}^u$ denotes the pixel of W_{I_z} at site u , and T is the threshold. The estimation of $W_{I_z}^u$ is refined during the second step, using Wiener filtering as

$$\max\left(\frac{(\tilde{W}_{I_z}^u)^2 - \sigma_W^2}{(\tilde{W}_{I_z}^u)^2}, 0\right) \cdot \tilde{W}_{I_z}^u \quad (33)$$

where σ_W^2 is the noise variance in the wavelet domain. Therefore, InSAR BM3D filters possess the superiorities of the NL and wavelet-domain filters. In addition to the wavelet-domain filter, other advanced methods have been proposed, such as pyramidal representation [87], higher-order SVD [24], and so on [88]–[92].

EXPERIMENTAL ANALYSIS

As an example of a typical method, the NL-InSAR algorithm proposed in [21] is applied to illustrate NL-filter performance. First, experiments are performed using the aforementioned data; the filtered images appear in Figure 11. The search-window size is 15×15 pixels, the patch size is 5×5 pixels, and $h = 12$. As Figure 11 shows, the NL-InSAR filter deals well with the smooth area that has little disturbance; however, there are filtered-phase artifacts in the high-heterogeneity and highly sloped areas. More experiments are implemented using the RADARSAT-2 repeat-pass interferometric sample data. Due to the resolution limitation, the search window size is 11×11 pixels, the patch size is 3×3 pixels, and $h = 6$. Figure 12 presents the filtered images and shows that NL-InSAR is very powerful for phase and amplitude denoising in areas with buildings.

REVIEW OF NEWLY ADVANCED METHODS

With the development of new signal processing concepts, such as sparse signal processing and machine/deep learning [93], [94], advanced methods have been proposed for InSAR phase denoising. Among them, sparse methods [95], [96] have drawn a lot of attention and shown potential. There is a high probability that these methods will make good candidates for the next generation of InSAR phase denoising.

The sparse methods can retrieve a noise-free image by applying a sparse constraint in a generalized formulation as

$$\min_{\mathbf{x}/\mathbf{s}, \Psi} \|\mathbf{s}\|_0, \quad \text{subject to} \begin{cases} \mathbf{x} = \mathbf{M}(\mathbf{z}_1, \mathbf{z}_2) \\ \mathbf{s} = \Psi(\mathbf{x}), \end{cases} \quad (34)$$

where $\|\cdot\|_0$ is the L_0 -norm of a vector; $\mathbf{x}/\mathbf{s}$ is the noise-free image to be recovered, containing the actual phase ϕ_x ; Ψ is a dictionary or operator to sparsely represent $\mathbf{x}$, $\mathbf{z}_1$; and $\mathbf{z}_2$ are the vectors of the interferometric pair of SAR images $\mathbf{z}_1$ and $\mathbf{z}_2$, respectively. In (34), $\mathbf{x} = \mathbf{M}(\mathbf{z}_1, \mathbf{z}_2)$ is a linear or nonlinear function derived by mapping $\mathbf{z}_1$ and $\mathbf{z}_2$ to $\mathbf{x}$, which can be treated as a uniform formulation of (9), (10), and (11). Accordingly, sparse technology can perform noise reduction on the real phase, complex phase, and interferogram, respectively. The direct solution of (34) is very difficult to calculate because it is a non-deterministic-polynomial time-hard problem. Solving (34) also depends on the forms of $\mathbf{M}$ and Ψ . In the following, two typical groups of sparse methods are discussed, considering their contributions.

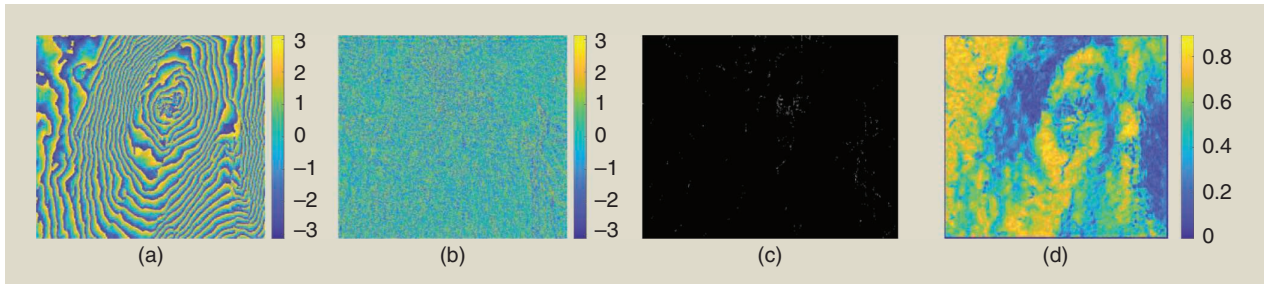


FIGURE 11. The filtered phase images obtained using the NL-InSAR filter [21] (Mount Etna data). The (a) filtered phase, (b) phase difference, (c) residues, and (d) coherence of the filtered images.

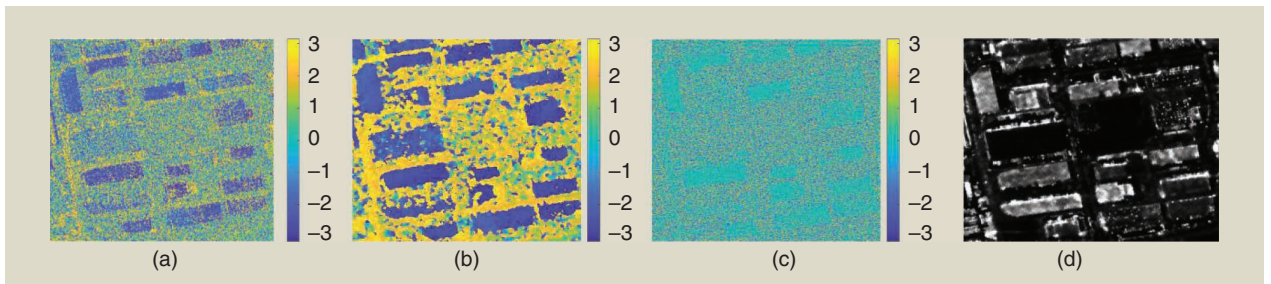


FIGURE 12. The filtered images obtained using the NL-InSAR filter [21] (RADARSAT-2 data). The (a) original phase, (b) filtered phase, (c) phase difference, and (d) filtered amplitude.

SPARSE REGULARIZATION

These sparse methods employ Bayesian rules to restore the filtered image through a maximum a posteriori (MAP) estimator [97]–[100]. Usually, the MAP estimation is transferred to solve an energy-minimum problem, which can be expressed in a generalized formulation as

$$\min_{\mathbf{x}} E(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x}) \\ E(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x}) = \Phi(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x}) + \kappa \cdot \|\Psi(\mathbf{x})\|_1, \quad (35)$$

where $\Phi(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x})$ is the data-fidelity term from the likelihood function, $\|\Psi(\mathbf{x})\|_1$ is the L_1 -norm term using a sparse prior, and κ is a regularized coefficient to balance the two terms. In (35), $\Phi(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x})$ usually have three different formulations according to the noise reduction in different domains. Taking the interferogram regularization as an example, $\Phi(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x})$ can be derived from a joint likelihood of (5) as

$$\Phi(\mathbf{z}_1, \mathbf{z}_2, \mathbf{x}) = \sum_{a_1 \in [z_1], a_2 \in [z_2], \phi_z \in \phi_z} 2 \log R + \frac{a_1^2 + a_2^2 - 2a_1 a_2 \beta}{R(1 - \gamma^2)}, \quad (36)$$

where $\mathbf{x}$ is composed of R and ϕ_x [involved in β , shown as (4) and (5)]. On the other hand, the format of $\|\Psi(\mathbf{x})\|_1$ greatly determines the regularization power. There are many different sparse-regularization approaches, such as total variation (TV) and wavelet-domain regularizations.

TOTAL VARIATION REGULARIZATION [23], [98]

Usually, TV regularization applies the gradient operation on the 2D phase image for noise reduction, which is expressed as

$$\|\Psi(\mathbf{x})\|_1 = \sum_u |\nabla(\phi_x^u)|, \quad (37)$$

where $\nabla(\phi_x^u)$ denotes the 2D gradient operator on phase ϕ_x at site u . The phase denoising benefits from the local smooth effect using the gradient operation. To improve the robustness of the phase reduction, the joint TV regularization of the phase and amplitude of InSAR data has been studied, with the regularization formulated as

$$\|\Psi(\mathbf{x})\|_1 = \sum_u \max(|\nabla(\sqrt{R^u})|, \lambda \cdot |\nabla(\phi_x^u)|), \quad (38)$$

where $\sqrt{R^u}$ denotes the pixel of amplitude image R at size u , and λ is used to balance the regularization between the amplitude and phase. Sparse TV regularization is not well suited to phase denoising for scenes that include high topography and high heterogeneity because it does not satisfy the sparsity assumption on the phase gradient.

WAVELET-DOMAIN REGULARIZATION [100], [101]

The generalized formulation of sparse wavelet regularization is given by

$$\|\Psi(\mathbf{x})\|_1 = \sum_u |W_x^u|, \quad (39)$$

where W_x^u denotes the pixel of wavelet image W_x at site u . In this framework, the phase-noise reduction is achieved by sparse regularization of the phase in the wavelet domain. The amplitude and phase can be jointly regularized in the wavelet domain to improve the sparsity degree, which is helpful to noise reduction. Accordingly, both amplitude and phase-noise reduction can be achieved through this approach.

SPARSE CODING

As opposed to sparse regularization, which uses a fixed dictionary, sparse-coding methods employ the dictionary learning of Ψ to improve the sparse representation of the phase image. The generalized formulation is shown as [102]–[104]

$$\min_{s, \Psi} \sum_u \|y_u - \Psi s_u\|_2^2 + \kappa_u \cdot \|s_u\|_1, \quad (40)$$

where y_u is a vector of one patch of InSAR observations (that is, S_z/I_z) centered at site u , and s_u is the corresponding patch of the noise-free image. The processing flowchart for the sparse-coding methods can be summarized in three steps:

- 1) for each pixel, collect the square window patch and arrange it in a vector form
- 2) use all of the patches for sparse coding to obtain the filtered results with a perfect sparse-signal estimation
- 3) aggregate the filtered patches to their original locations through data fusion. In this manner, the filtered phase image can be obtained.

EXPERIMENTAL ANALYSIS

Two sparse-regularization algorithms are employed to illustrate the sparse methods' performance. First, experiments based on RADARSAT-2 data are performed using sparse TV [23] and wavelet [100] regularizations. Figure 13 presents the filtered results and shows that both algorithms can effectively reduce noise in urban areas. Next, the wavelet regularization is applied to the Mount Etna interferometric data, and the filtered results are given as Figure 14.

For clarity, Figure 15 provides more details of the algorithms' results. As Figure 15 shows, the Lee filter introduces some artifacts of fringes that are ambiguous and broken in areas that have a high topography and low coherence. Compared to the wavelet filter, the region-growing and sparse-wavelet methods can improve the performance of interferometric phase-noise reduction in smooth areas and effectively suppress the phase residues of grainy noise. The sparse-wavelet method has the best performance for dealing with blurring and the discontinuities of the phase fringes. More details can be found in [100].

COMMENTS

In addition to the sparse methods, other technologies have been tried in InSAR phase denoising, such as the Markov random field [105]–[108], tensor decomposition [109], convolutional neural networks [110], and optimization integration with phase unwrapping [111]–[115]. Most of them can be roughly classified as machine- and

deep-learning methods, and their details are not included in this article.

CONCLUSIONS AND PROSPECTS

In this article, we reviewed InSAR phase-denoising technology. During the past few decades, numerous methods have been implemented, including traditional local filters,

transformed-domain filters, NL filters, and others. We introduced the concepts behind these methods and surveyed the strengths and limitations of each process, theoretically and experimentally. Research achievements in InSAR phase denoising look exciting; however, there is room for improvement in fields such as NL filters and the upcoming technology of newly advanced methods. In the following,

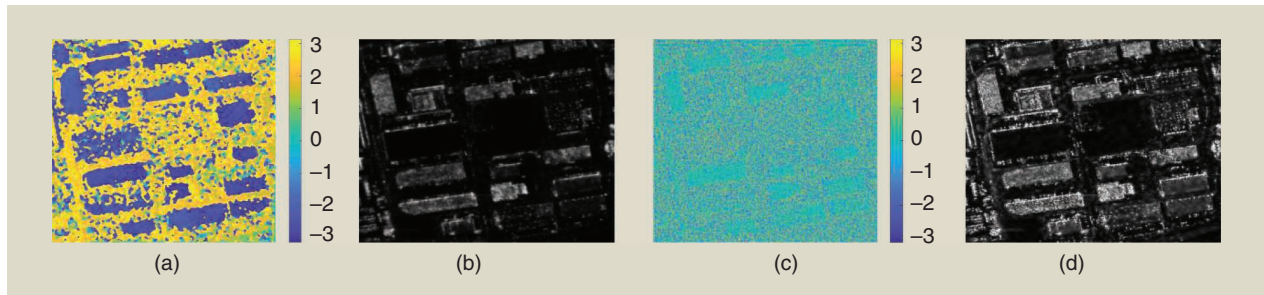


FIGURE 13. The filtered images obtained using the sparse methods (*RADARSAT-2* data). TV regularization [23]: (a) the filtered phase and (b) the filtered amplitude. Wavelet regularization [100]: (c) the filtered phase and (d) the filtered amplitude.

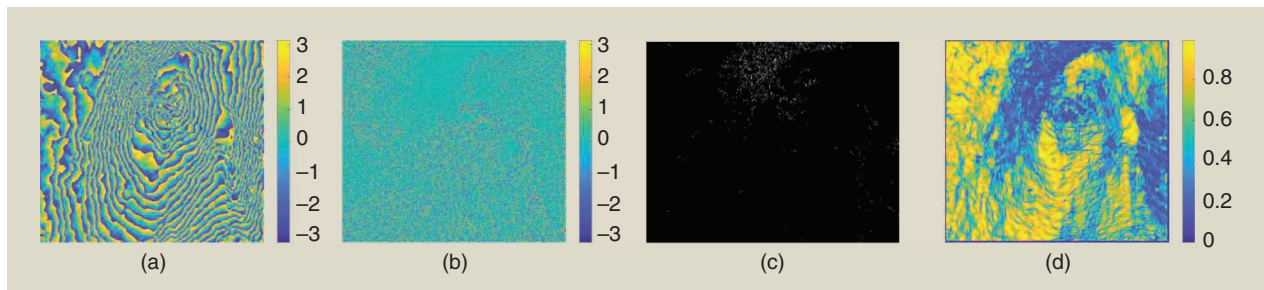


FIGURE 14. The filtered phase images obtained using sparse-wavelet regularization [100]. The (a) filtered phase, (b) phase difference, (c) residues (3,773), and (d) coherence of the filtered images.

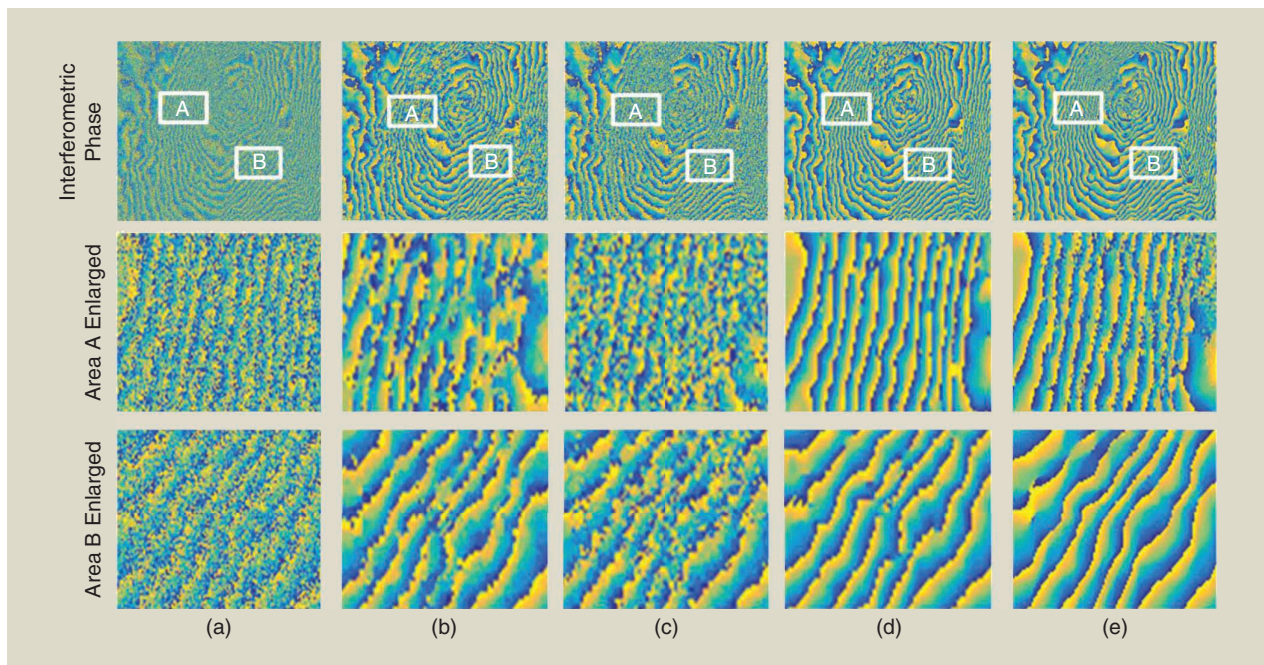


FIGURE 15. The filtered phase images that were derived through various methods (Mount Etna data) [100]. (a) The original. (b) The Lee filter [13]. (c) The wavelet filter [29]. (d) The region-growing method [60]. (e) The sparse-wavelet regularization [100].

we provide some research suggestions and identify potential future directions.

HIGH-EFFICIENCY AND HIGH-PRECISION ALGORITHMS

NL filters use the patch-wise strategy for selecting samples and the iterative manner to improve their estimation performance. In practice, the filter parameters (such as the search-window and patch sizes, similarity-measurement criteria, and iteration number) are crucial to the efficiency and precision of the algorithm implementation. In particular, the complicated texture of interferometric images, which have a significant topography variation and high heterogeneity, challenges NL filters, hindering their practical application [116]. Therefore, improving robustness and efficiency is an important issue for NL filters as well the other phase-denoising methods.

SPARSE METHODS

The sparse methods' performance is highly dependent on the model of a sparse prior. The sparse representation of interferometric images remains an open question. It is hard to evaluate the sparse solution of the interferometric phase because 1) the sparse results depend on the sparse signal recovery technique, such as sparse regularization and coding; and 2) it is difficult to distinguish the interferometric phase from noise in the sparse space, since there is no explicit theoretical support. Therefore, designing a paradigm for the sparse phase denoiser is essential to promote practical development of the technology. Achieving a high efficiency is also an important factor.

EVALUATING PHASE-DENOISING PERFORMANCE

It is commonly accepted that a method to objectively evaluate phase-denoising performance remains elusive. The purpose of phase denoising is to reduce noise and preserve phase details as much as possible. In flat areas, noise reduction is the most important issue. In high-topography regions, preserving phase details without introducing artifacts becomes more important. Computational complexity is a significant matter, too. Further study is required to develop the best technique to comprehensively evaluate phase-denoising performance, which would benefit architecture development of InSAR signal processing.

Phase-denoising technology plays an important role in InSAR signal processing, satisfying practical demands and contributing to the development of new systems. The purpose of this article is to provide researchers with guidelines as well as inspiration. It is our hope that this article can help to promote the development of InSAR technology.

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IT IS COMMONLY ACCEPTED THAT A METHOD TO OBJECTIVELY EVALUATE PHASE-DENOISING PERFORMANCE REMAINS ELUSIVE.

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