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ABSTRACT

Speckle reduction is a major issue for many SAR imaging applications using amplitude, interferometric, polarimetric or tomographic data. This subject has been widely investigated using various approaches. Since a decade, breakthrough methods based on patches have brought unprecedented results to improve the estimation of radar properties. In this paper, we give a review of the different adaptations which have been proposed in the past years for different SAR modalities (mono-channel data like intensity images, multi-channel data like interferometric, tomographic or polarimetric data, or multi-modalities combining optic and SAR images), and discuss the new trends on this subject.

Index Terms— patch-based approaches, SAR despeckling, NL-SAR.

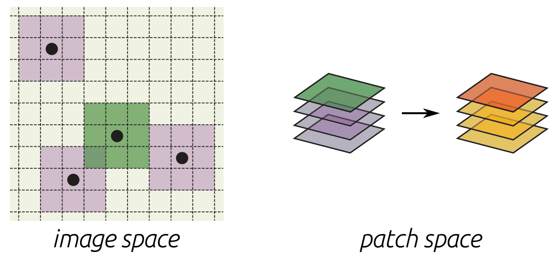

Fig. 1: Principle of non-local approaches. On the left, the denoising of the central pixel of the green patch is achieved by using the information carried by similar patches (purple) found in a search window. On the right, in some more evolved versions, stack of patches are jointly processed to obtain filtered stacks.

1. INTRODUCTION

SAR imaging is a coherent imaging system leading to the well known speckle phenomenon due to the complex summation of interacting waves in a resolution cell. Fortunately, well-grounded statistical models have been proposed to characterize the SAR measure variability [1]. Relying on these models, families of speckle reduction filers have been developed in the past years: regularization based approaches (for instance with minimum total variation [2]), signal decomposition methods (with wavelets or curvelets [3]), or selection based filters. Among this last family, the patch-based selection filters have become extremely popular since the seminal paper of Buades et al. [4]. Instead of using an advanced model of the statistical distribution of images, these methods rely on a far simpler redundancy assumption. By looking for similar local configurations, extremely efficient denoising approaches can be formulated.

The first approach, known as "NL-means" [4] proposed the following scheme: to process a given pixel, similar patches in the image are searched and the central values of these similar patches are averaged (see fig.1). The three main parameters of the initial NL-means are the following: the patch size controlling the similarity scale, the search window controlling the neighborhood in which similar pixels are selected, and the smoothing strength controlling the selectivity of the pixel selection (see fig. 2). Based on self similarity, the main limit of this scheme is the "rare patch effect" when no similar patch can be found, leading to residual noise in the result.

The extremely powerful principle of NL-means based on image redundancy led to breakthrough results in denoising and numerous adaptations of this core idea have been proposed: grouping of similar patches and joint denoising [5], parameter adaptation [6], Bayesian modeling of the patch distribution [7], dictionaries of patches [8], dictionaries of distributions (like Gaussian Mixture Models) for patches [9], patch shape adaptation [10], etc.

The previously mentioned contributions are mostly dealing with additive white Gaussian noise and applications in computational photography [11]. First adaptations to non-Gaussian noise can be found in [12] for speckle in ultrasound, [13] for Poisson noise and [14] for gamma noise. Nevertheless, the processing of complex data such as vector of complex values of SAR imaging is not straightforward. In the following sections, we present the adaptations of the NL-means framework to different SAR data. Most of them are based on a complex distribution for the back-scattered electro-magnetic field z for a given reflectivity R of the scene,

$$p(z|R) = \frac{1}{\pi R} \exp\left(-\frac{|z|^2}{R}\right) ,$$

leading to gamma distribution for intensity value. For a vector of complex values $k = (z_1, z_2, ..., z_K)^t$ a multivariate circular complex Gaussian distribution is often assumed:

$$p(k|\Sigma) = \frac{1}{\pi^K |\Sigma|} \exp\left(-k^\dagger \Sigma^{-1} k\right) ,$$

Σ being the covariance matrix containing the physical parameters of interest (interferometric or polarimetric parameters depending on the K channels). When averaging the Hermitian product of L samples, a multi-look data is obtained which follows a Wishart-distribution. All these distributions are very helpful to define well-grounded patch similarity criteria and sample-based estimators.

Previous reviews of non-local methods for SAR imaging can be found in [15] and [16] for instance. Besides, due to space constraints, the references of this paper are far from exhaustive on the subject.

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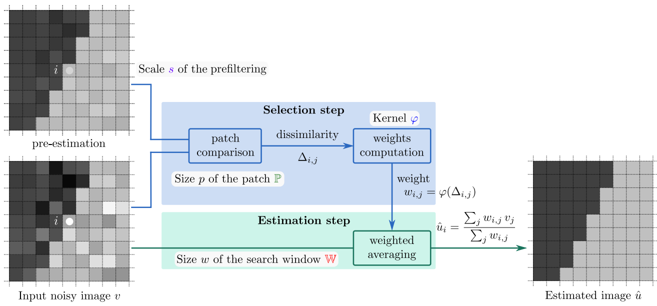

Fig. 2: Steps of patch-based methods (selection step and estimation step). In addition to the noisy image, a pre-filtered image is often used to ease the patch comparison, especially for high levels of noise. From the dissimilarity between patches, a kernel is applied to convert them to weights (a low dissimilarity implying a high weight). All the indicated parameters (size of the patch, size of the window search, kernel shape, prefiltering strength) have an influence on the obtained result.

2. AMPLITUDE OR INTENSITY IMAGES

When dealing with amplitude images, two adaptations of the original NL-means [4] have to be done: the adaptation of the estimation formula and the adaptation of the similarity between two patches. These adaptations are necessary to take into account the specific distribution of the data (Rayleigh-Nakagami for amplitude and Gamma for intensity images). Without them, filtering parameters can not be adjusted so as to produce satisfactory results both in bright and dark regions.

In [14], a probabilistic framework is developed both for the estimation step, relying on a weighted maximum likelihood estimation, and for the patch similarity, reformulated as a generalized likelihood test (GLRT) [17]. We will see in the following that these adaptations are very general and can be straightforwardly applied when dealing with complex vectorial data such as polarimetric or interferometric data. A refinement is also proposed in [14] by using an iterative framework in order to gradually improve the similarity estimation based on the restoration at the previous iteration. This is done by adding a Kullback-Leibler divergence term in the patch similarity computed on the on-going filtered result. This combination improves drastically the patch weight estimation and leads to results with a better preservation of fine structures.

Although providing an improvement, this iterative framework is difficult to control (for instance the setting of the number of iterations), and is still influenced by the parameters (patch size, window search, selectivity). Indeed, there is no general parameter setting and the parameters have to be adapted to the scene content. A framework for automatic parameter selection is proposed in the NL-SAR framework of [18]. It relies on the estimation of numerous restoration results for a wide range of parameters and a selection strategy based on variance minimization after a debiaising step.

In [19], an adaptation of BM3D [20] working on stacks of patches is proposed, relying on the GLRT patch similarity and adapted distributions after the wavelet transforms to take into account the multiplicative noise.

Other approaches have proposed to compare the distributions inside the patches to define the weights (for instance [21]). This way loses the structural organization of the patch to the advantage of an increased robustness to noise. In [22] a sigma-preselection is done to select the patch samples.

3. INTERFEROMETRIC AND TOMOGRAPHIC DATA

Interferometry is a tremendous modality for SAR imagery, providing information on object elevation and movement by phase difference computation between two geometrically close acquisitions. As the amplitude data, interferometric data are subject to strong fluctuations and many filtering approaches have been proposed to improve interferometric phase and coherence estimation.

Non-local approaches have provided state-of-the-art results for interferometric data. In [23], a GLRT criterion is used to select the similar noisy patches associated with a weighted likelihood estimation of the covariance matrix. To refine the weight computation, in addition to the similarity between noisy patches, the on-going estimated result is used through a Kullback-Leibler divergence criterion similarly to [14].

In [18] and the NL-SAR generic framework, this refinement is replaced by the selection of the best estimate minimizing the variance inside a range of estimates for a set of parameters covering scene diversity.

In [24], improvements are proposed through the compensation of the deterministic, topographic phase component, leading to a better selection of the statistically homogeneous pixels for high resolution DEM generation. A similar idea is developed in [25].

In [26], the non-local approach is combined with a regularization model (minimization of the Total Variation) taking into account the spatially variant speckle reduction.

Dealing with multi-baseline data with slightly different angles and high coherence allows to do tomographic reconstruction, giving the elevation of all the scatterers inside the 3D resolution cell. This is particularly useful in dense urban areas where lay-overs severely limit the interferometric potential. The 2-channels interferometric case can be directly extended to process K-dimension tomographic stacks. Nevertheless, the curse of dimensionality quickly hinders the efficiency of the patch-based methods. Indeed, comparing 3D cubes (with a size equal to the size of the patch multiplied by the number of channels) leads to very few similar samples, thus drastically reducing the noise filtering. Therefore, tomographic filtering is often reduced to interferometric filtering between pairs of images. Examples of the use of patch-based approaches for SAR tomography can be found in [27], [28] and [29].

4. POLARIMETRIC DATA

Like interferometric data, polarimetric data are a special case of multi-channel complex data and Wishart-distributed covariance matrices. Therefore, similar frameworks can be applied. In [30], a GLRT is applied with a threshold to suppress the less similar samples, and in [18] the general NL-SAR framework already mentioned is applied.

In [31], adapted stochastic distances are proposed for the patch comparison. The idea is to compute geodesic distances on the cone of positive Hermitian matrices. In [32], weights are iteratively refined based on the ratio of diagonal elements of empirical covariance matrices and the span of the previous iterate.

Extensions to PolInSAR data have also been proposed [18], keeping in mind the reduction of the number of similar samples as the dimension increases.

In [33] the shape of the patches is locally adapted to improve the restoration results and the polarimeric parameters preservation.

5. MULTI-TEMPORAL SAR SERIES

Multi-temporal SAR series can be considered as a special case of multi-channel data with no correlations between the channels. In this case the aim is the recovery of the best reflectivity image for each date. Again, due to the increase of the dimension, it can be shown that a straightforward application of 3D (space and time) patch comparison is not very efficient and leads to a limited noise reduction. Another approach, instead of considering a 3D cube, is to keep 2D patches but to increase the search window using the time dimension. This increases the size of the search space (hence, the computational complexity) and is not very efficient when dealing with a high level of noise. Indeed, the selection in itself is not improved by the increase of the searching space. A more efficient method is to take benefit of the time redundancy to improve a first estimation of the data, thus improving the further selection step [34]. In [35], a grouping of patches and collaborative filtering followed by an aggregation step is done in time and space dimensions.

Another adaptation to multi-temporal series is the framework proposed in RABASAR [36]. The idea is to use a patch-based approach for a ratio image. To this aim, the MuLoG method proposed in [37] can be applied with an adaptation to the distribution of ratio images. More generally, MuLoG allows the use of any patch-based method dedicated to additive white Gaussian noise as a denoiser in its framework.

6. HYBRID DATA

The framework of non-local approaches is very general and can be used to combine different sensors, like optical and SAR data, or multi-sensor SAR data. Indeed, the patch comparison and the weight computation can be driven by an auxiliary data to help the selection of the similar samples. This idea is developed in [38] using an optical image to guide and constrain the patch comparison. The results of SAR despeckling can be greatly improved but a fine registration is usually necessary and the different behaviours of the sensors have to be carefully taken into account.

Other attempts could be done in this direction, like for instance the use of a multitemporal stack to guide the weights of a specific SAR date.

7. CONCLUSION

The patch-based approaches have had a considerable success in the past years for SAR image speckle reduction. Numerous variants have been proposed (many of them being not referenced in this review) for all the SAR modalities, amplitude, interferometry, polarimetry, tomography. There is still active research on the parameters setting, the overcoming of the rare patch effect when the dimension increases, the introduction of external knowledge and the adaptation to specific applications by introducing physical constraints on the problem to solve.

Several hot research topics are to be mentioned. The correlation of the speckle noise has to be taken into account to avoid un-expected structures linked to noise correlation to be enhanced by the filtering step. A sub-sampling step or more advanced processings can be applied [39] [40]. The variable number of looks of the data is also an issue (for instance after a preliminary filtering step or temporal processing).

On the contrary to the previous generation of filtering methods, non-local patch-based methods do not rely on image handcrafted models but on the image redundancy property which is far less restricting, the filtering step in itself being often reduced to its simplest expression (weighted averaging). In the past 5 years, a new family of methods has emerged with the deep convolutional neural networks. Interestingly, neural networks go back to modeling through a learning step fed by thousands or millions of samples. Although having already brought impressive results [35] [41], these methods still present some drawbacks. They need a huge amount of data for training. This problem will probably be solved in the next years but the generalization to different sensors (resolutions, incidence angles, polarizations,...) has to be handled carefully. For very high levels of noise, like 1-look images, deep neural networks are too creative, sometimes inventing new information like point-like scatterers or structures. This may be due to the "limited" amount of training samples but this point is of utmost importance for real applications of SAR imaging. Therefore, a possible way is probably the combination of redundancy based methods and deep-learning, each one being able to control the other. Different strategies can be envisaged in this framework as can be seen in [42] and [43].

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