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# How to handle spatial correlations in SAR despeckling?

## Resampling strategies and deep learning approaches

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### Abstract

Speckle noise strongly affects Synthetic Aperture Radar (SAR) images, causing strong intensity fluctuations that make them difficult to analyze. Although many speckle reduction algorithms have been proposed, how to effectively deal with the spatial correlations of speckle remains an open question, especially in the most recent deep learning approaches. This paper tries to address this problem. Existing approaches to tackle the speckle correlations are described. Then, a standard training strategy for deep learning is proposed. Two models are trained and the increased robustness brought by including a Total Variation (TV) term in the loss function is analyzed on Sentinel-1 images.

## 1 Introduction

Earth observation, damage assessment, biomass estimation are a few examples of fields that benefit from the use of Synthetic Aperture Radar (SAR) images. SAR sensors have the ability to acquire data at any time and under (almost) all weather conditions, allowing for a continuous and constant coverage of the Earth surface. With the launch of the sensors of the Sentinel family and their accompanying open access policy, a huge amount of data are continuing released, fueling the research in several domains such as climate change studies.

However, SAR images are difficult to interpret. Indeed, single-look SAR images display a strong multiplicative noise, the so-called speckle. One may object to the use of the term "noise", since techniques such as interferometry retrieve useful information from the correlations between those fluctuations in two images acquired at slightly different incident angles. Yet, when considering a single intensity image, speckle fluctuations impede the application of standard image processing technique and require some denoising step.

There exist different strategies to tackle this denoising problem. Bayesian approaches rely on a statistical model of the reflectivities and of the speckle component. Such methods have been developed both in the spatial domain and in some transformed domain and include the regularization techniques. Among non-Bayesian approaches we can find morphological filters and approaches resorting to machine learning, in particular methods based on deep neural networks.

In the literature, a great effort has been devoted to speckle suppression over the last decades. The simplest operation is called multilooking and consists in averaging a number of independent acquisitions to reduce the noise fluctuations while preserving the mean intensity value. Multilooking

can be applied either (i) in the temporal domain, when several images are acquired over an area where no significant changes have occurred, (ii) in the spatial domain, by averaging pixels (or linearly combining them [1] [2] [3] [4] [5] [6]) within a fixed window, or (iii) in the spectral domain (by averaging intensity images obtained from sub-aperture synthesis). However, temporal stability is rarely reached (reflectivities vary during time due to changes such as vegetation growth or soil moisture evolution), which limits the direct application of (i), and spatial (ii) or spectral (iii) multi-looking severely degrade the spatial resolution.

The more sophisticated non-local approaches, that rely on an adaptive selection of noisy patches to estimate the noise-free image, have more recently been proposed. Among them, we can cite the PPB filter [7] and its extensions to interferometry [8] and polarimetry [9], NL-SAR [10], SAR-BM3D [11], which extends the block-matching 3D algorithm to take into account the specificities of SAR images, but also [12, 13, 14] and MuLoG [15], which proposed a general scheme to include any Gaussian denoiser in an iterative process to remove speckle from SAR acquisitions. Most recently, the advancements of deep learning algorithms for image restoration, in particular for additive white Gaussian noise (AWGN) suppression, has motivated several extensions to radar imaging [16, 17, 18, 19, 20]. Deep learning algorithms require a lot of training data, namely pairs of clean-noisy images, in order to generalize well. This makes it non-trivial to extend approaches initially developed for computer vision. In particular, several issues need to be addressed: the scarcity of noise-free images in remote sensing, the high dynamic range of SAR images, the statistical distributions that strongly differ from those observed on natural images, or the differences that occur when considering different sensors.

This paper is devoted to reviewing the strategies that are applied in the despeckling algorithms in order to handle the

spatial correlations of speckle. Given the numerous recent works in despeckling methods based on deep-learning, we focus a part of our discussion on those approaches. In the first section, we recall the statistical model of speckle noise that underlies most methods. Then, the problem of the spatial correlations is made evident by applying on Sentinel 1 images some speckle reduction methods that assume speckle decorrelation. Strategies to mitigate the impact of speckle correlations are then described and a more extensive analysis on deep learning is provided.

## 2 Speckle model

Inside a resolution cell, several scatterers indistinguishable from the system are present, and each one yields a backscattered echo. The radar does not resolve each individual contribution but only measures the sum of all backscattered echoes, i.e.,  $A \exp j\phi = \sum_i A_i \exp j\phi_i$ . Since the phases are highly varying and can sum in a constructive or destructive way, the amplitude of the resulting signal seem to vary randomly [21].

Under the assumption of a large number of independent and identically distributed scatterers, Goodman *et al.* [22] developed the fully-developed speckle model where the measured intensity  $I$  is related to the underlying reflectivity  $R$  and the speckle  $S$  by the multiplicative model

$$I = RS, \quad (1)$$

where the speckle component  $S$  follows a Gamma distribution described by:

$$p(S) = \frac{L^L}{\Gamma(L)} S^{L-1} \exp(-LS), \quad (2)$$

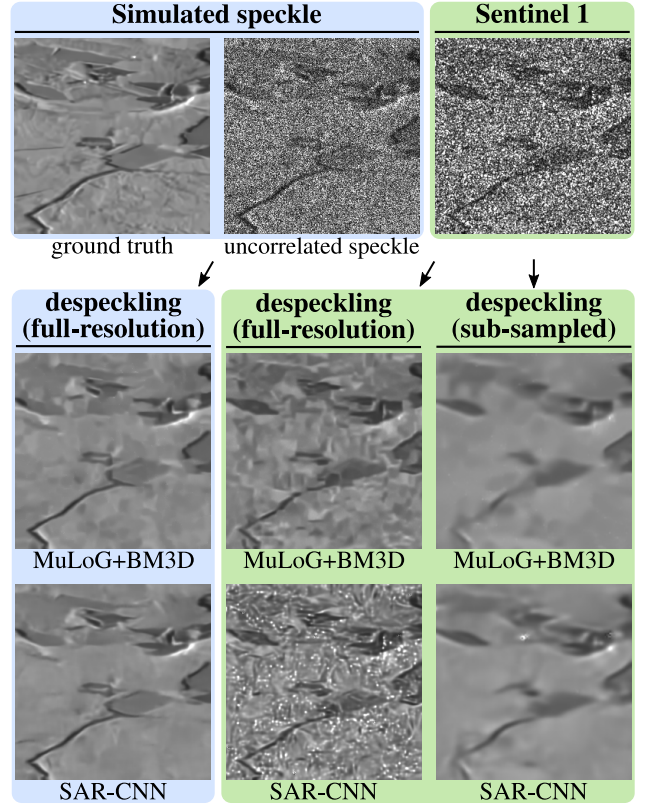
where  $L \geq 1$  represents the number of looks and  $\Gamma(\cdot)$  is the gamma function. It follows that the component  $S$  has unitary mean and a variance that is inversely proportional to the number of looks:  $\text{Var}[S] = 1/L$ . The speckle component  $S$  at each pixel of the SAR image is assumed to be independent and identically distributed (i.i.d.).

This model is the funding statistical model of the speckle reduction techniques developed in the last decades. The i.i.d. assumption is certainly the least representative of real SAR imaging system [21]. During the synthesis of a SAR image (i.e., the focusing of the radar image), some oversampling and spectral windowing are applied in order to produce an image with a given pixel size and with limited sidelobes [23]. As a downside, these operations introduce spatial correlations in the speckle [24]. Speckle reduction methods therefore require some adaptation in order to be robust to these correlations.

## 3 Speckle reduction in the presence of spatial correlations

### 3.1 Illustration of the problem

One-look SAR images are strongly affected by speckle noise. Most recent speckle reduction techniques are quite



**Figure 1** Recent speckle reduction methods such as MuLoG or SAR-CNN perform very well on simulated speckle (left column, in blue). Direct filtering of real images however leads to many artifacts, as illustrated on this single-look Sentinel 1 image (central column, in green). Sub-sampling the image by a factor 2 reduces the speckle correlations and lead to a much better restoration, at the cost of a resolution loss (right column, in green).

effective at removing most of these fluctuations, when evaluated on synthetic speckle, see left column of Fig. 1. Direct application of these methods on a real image leads to serious artifacts, see the despeckling results obtained on a Sentinel-1 image shown on the central column of Fig. 1. Those artifacts are due to the mismatch between the theoretical model of speckle considered (i.i.d. speckle component) and the actual speckle component (spatially correlated due to oversampling and spectral windowing).

A simple method to reduce the impact of the spatial correlations of speckle is to downsample the SAR image. A good compromise between reduction of correlation and preservation of resolution is to apply a downsampling factor of 2, as shown in Fig. 1, right column. The artifacts are suppressed, however the resolution is not as good as the resolution achieved on the numerical simulation where no downsampling was necessary.

Another example of artifacts due to spatial correlations of the speckle can be seen in the paper [17], where PPB algorithm and SAR-CNN do not perform as expected because no downsampling is applied to the real image.

These examples show that it is essential to ensure that the speckle has no significant spatial correlations prior to applying some speckle reduction methods from the literature.

In the next section, alternative solutions to downsampling are analyzed.

### 3.2 Strategies to denoise SAR images with correlated speckle

One possibility to successfully apply algorithms based on Goodman's fully developed model and the i.i.d. assumption is to revert the steps performed by the data providers. In [24] and [25], Abergel *et al.*, provide a method that preserves the spatial resolution by correctly resampling SAR images and extracting bright targets. A so-called pseudo-raw image is then recovered, which is the image that would have been acquired if the data was sampled at the Shannon-Nyquist sampling frequency and no spectral weighting was applied (i.e., no *apodization*). Based on the knowledge of the parameters of the sensor contained in the metadata of the images, *deramping*, *demodulation* and *deapodization* can be carefully computed to obtain an image where, in homogeneous regions, speckle presents almost no spatial correlation [25]. The pseudo-raw image can then be filtered using standard speckle reduction methods. The over-sampling factor and the spectral apodization can be re-applied to the resulting image in order to obtain an image comparable to the original image.

This approach applies pre- and post-processing steps that require the knowledge of sensor's parameters and are sensor-specific. However, this is not always the case. In [26], Lapini *et al.* propose a blind speckle decorrelation algorithm. After having detected and removed the point targets according to a threshold empirically set, least square (LS) optimization is performed to estimate and invert the point spread function (PSF) of a SAR acquisition system. At this step, the reflectivity can be estimated by filtering the image with a despeckling algorithm developed under the uncorrelated speckle hypothesis. As the PSF is applied independently on each polarimetric channel, Arienzo *et al.* [27] have extended this method to PolSAR data.

These methods, however, come at a computational cost. If one wants to process an image in a more automatic and straightforward way, the despeckling algorithm has to include some robustness to spatial correlations. In NL-SAR [10], robustness to noise correlation is granted by an adaptive kernel that is learned by analyzing a homogeneous area in order to map patch similarities to weight and account for the improved similarities observed when speckle gets spatially correlated. NL-SAR generalizes non-local approaches which combine similar patches to reduce speckle fluctuations. Beyond the adaptation of the kernel that maps similarities to weights, when the speckle is correlated, larger patches and extended search areas are considered to maintain a satisfying noise suppression, see [10].

NL-SAR gives its best in polarimetric and interferometric configurations. In the case of single-channel SAR (intensity) images, deep learning approaches represent the current state-of-the-art. Various attempts to obtain an algorithm robust to correlations have been made. Chierchia *et al.* [16] propose to create an ad-hoc dataset to train their model, named SAR-CNN, by exploiting a large stack of multitemporal data. By selecting regions where no

changes have occurred, an almost speckle-free reference is produced by multitemporal multilooking. The network is then trained to reproduce the speckle-free reference images starting from the actual observations. This approach requires the availability of a large number of acquisitions on the same area and the definition of "no changes" is not well-defined.

Multitemporal stacks without changes are also exploited in the work of Boulch *et al.* [19], where a general denoising framework requiring no groundtruth data is proposed. It is based on the intuition that, if a network is trained to reproduce a speckled image from another speckled image representing the same scene, it will end up producing a speckle-free data. The use of real acquisitions allows the network to also learn the spatial correlation structure of the speckle component.

Other training strategies have also been proposed [17, 18, 20]. No standard exist yet in deep learning for SAR image despeckling, which also makes it difficult to compare different architectures and reproduce the published results. In the next section, we propose a standard training strategy and analyze the impact of including in the training loss the Total Variation (TV), defined in equation (4), to attenuate the effect of the correlation.

## 4 Deep Learning for SAR image despeckling: training methodology and robustification with TV

In [17] and [18], natural images corrupted with synthetic speckle noise are used to generate noisy SAR-like data. In [20], natural images are used to pre-train the network, which is then fine-tuned using SAR images: stacks of data are averaged to produce a clean reference and synthetic noise is added to them. To obtain the results that illustrate this paper, we implemented, instead, the following training strategy: a speckle-free reference is created by averaging a multitemporal stack of images acquired over the same scene and the remaining speckle fluctuations are suppressed using MuLoG+BM3D with the appropriate equivalent number of looks. No downsampling is performed, as this denoising step is applied on already multilooked data to suppress small fluctuations of speckle, limiting the influence of correlation. Synthetically generated speckled images are then created by following Goodman's model and the i.i.d. assumption and using the speckle-free reference images as images of the reflectivities  $R$ .

To study the role of a TV term in terms of improved robustness to speckle correlations, we have trained two models: the SAR-CNN introduced in [16] and the U-Net proposed in [28], with an addition of a residual skip connection. The logarithm of amplitude images are used as inputs to the networks. The networks are trained to extract the speckle component (this corresponds to a residual learning strategy). The estimated reflectivities can then be obtained from the speckled image and the speckle component. While images with simulated speckle are used during training, real single-look images (acquired over areas not belonging to

the training set) are used in the testing set. The networks are trained using two different loss functions in order to analyze their differences. In the first case, an  $\ell_1$  loss is used:

$$\mathcal{C}_{\ell_1} = \sum_{i=1}^N \|f_{\text{CNN}}(\tilde{\mathbf{y}}_i) - \tilde{\mathbf{x}}_i + (\psi(L) - \log(L)) \cdot \mathbf{1}\|_1 \quad (3)$$

where  $\tilde{\mathbf{y}}_i$  and  $\tilde{\mathbf{x}}_i$  are a pair of log-transformed noisy and clean amplitude images. Bias is corrected at the network's output. We define the Total Variation term on the denoised image  $f_{\text{CNN}}(\tilde{\mathbf{y}}_i)$  by:

$$\mathcal{C}_{\text{TV}}^\epsilon = \sum_{p,q} \left[ (f_{\text{CNN}}(\tilde{\mathbf{y}}_i)_{p+1,q} - f_{\text{CNN}}(\tilde{\mathbf{y}}_i)_{p,q})^2 + (f_{\text{CNN}}(\tilde{\mathbf{y}}_i)_{p,q+1} - f_{\text{CNN}}(\tilde{\mathbf{y}}_i)_{p,q})^2 + \epsilon^2 \right]^{1/2}, \quad (4)$$

where  $\epsilon$  is a parameter that is small compared to the typical contrast between log-transformed values. A joint loss that combines the two previous losses is defined by:

$$\mathcal{C}_{\ell_1+\text{TV}} = \mathcal{C}_{\ell_1} + \lambda \mathcal{C}_{\text{TV}}^\epsilon \quad (5)$$

The use of the Total Variation term is justified by its effectiveness in reducing spurious details, characterized by a high total variation, that strongly affect the estimations of the speckled image when speckle is correlated. Penalizing reconstructions with a large Total Variation improves the robustness while preserving sharp edges (which have a low total variation).

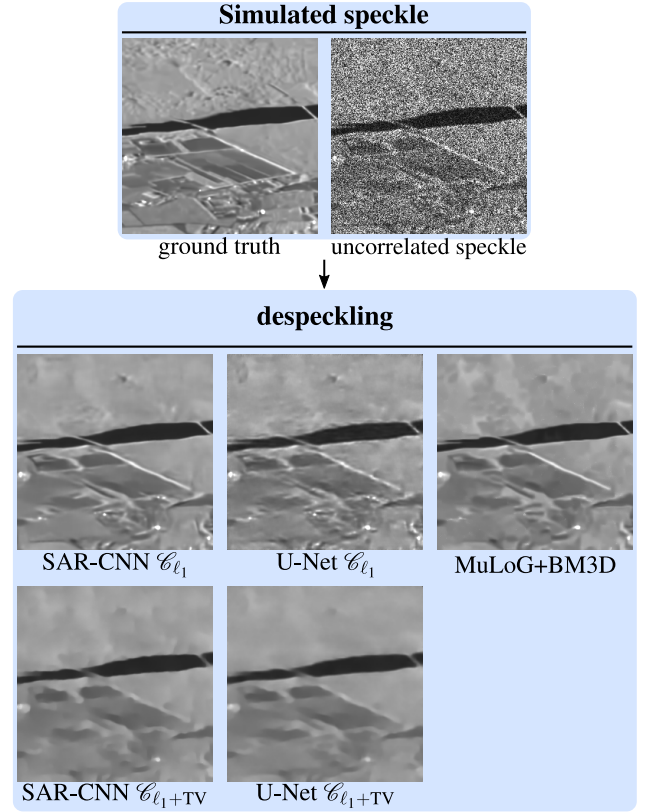
The two loss functions  $\mathcal{C}_{\ell_1}$  and  $\mathcal{C}_{\ell_1+\text{TV}}$  are tested on images with synthetic noise (Fig. 2) and real images (Fig. 3).

Adding the total variation terms has the effect of smoothing the results. In the simulations with synthetic speckle, this leads to the loss of some small details. However, when real images with correlated speckle are considered, the networks trained with the combined loss  $\mathcal{C}_{\ell_1+\text{TV}}$  lead to results with far fewer artifacts. In order to obtain this robustness, a large value of  $\lambda$  has been chosen ( $\lambda = 1.2$ ). Compared to the sub-sampling strategy, the results seem slightly worse. In particular the bright targets in Fig. 3 are well-preserved by SAR-CNN applied to a down-sampled image while they disappear when the TV term is employed.

## 5 Conclusions

In this paper we investigate different strategies that one can adopt when dealing with correlated SAR images. Down-sampling the image may seem to be a crude method, as it leads to an image with a poorer resolution, yet at the end it provides the best results when single-look images are considered.

When training a neural network with the Total Variation term in the loss function, the robustness to speckle correlations is improved, but this requires choosing a high value for the regularization parameter to avoid spurious structures in single look images. As a consequence, small details are not well preserved. This strategy seems more suitable when the number of looks is larger (see results proposed in [17]): this is the case of Ground Range Detected



**Figure 2** Results of MuLoG+BM3D and the two deep learning methods, SAR-CNN and U-Net, on an image with synthetic 1-look uncorrelated speckle

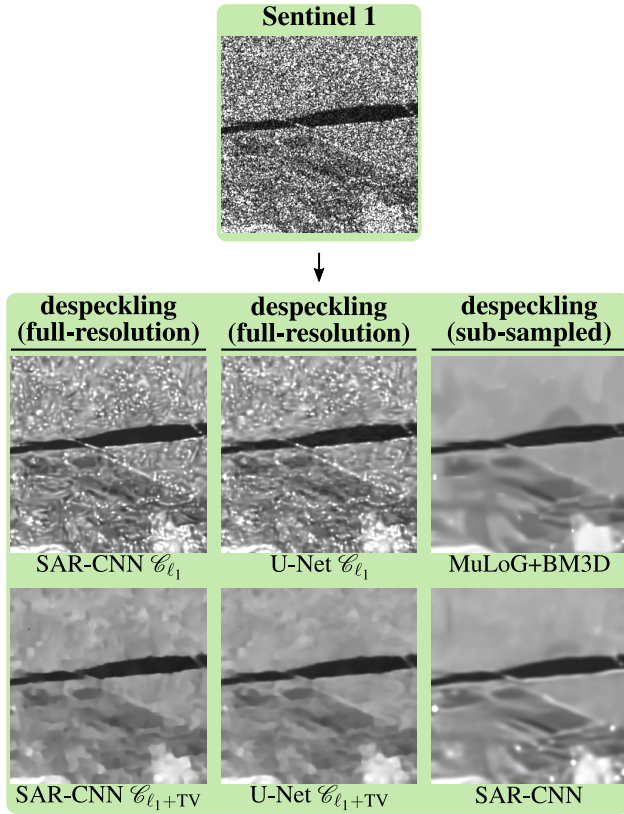
images, whose Equivalent Number of Looks is around 4. A much lower regularization parameter is then required to obtain results that are immune to the spatial correlations of speckle, and hence much fewer small details are lost in the restoration process.

In the future, it would be interesting to train a deep learning model specifically to denoise correlated data. The strategy proposed to create an ad-hoc training set of SAR images can be extended to include the resampling method discussed in section 3.2, allowing the learning from images generated with a synthetic correlated speckle noise. An alternative approach would be to exploit multitemporal series of SAR images to learn to reduce speckle noise directly from the real SAR images.

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**Figure 3** Results of MuLoG+BM3D and the two deep learning methods, SAR-CNN and U-Net, on a real 1-look Sentinel-1 image

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