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ABSTRACT

In this paper, a generic method is proposed to reduce speckle in multi-temporal stacks of SAR images. The method is based on the computation of a "super-image", with a large number of looks, by temporal averaging. Then, ratio images are formed by dividing each image of the multi-temporal stack by the "super-image". In the absence of changes of the radiometry, the temporal fluctuations of the intensity at a given spatial location are due to the speckle phenomenon. In areas affected by temporal changes, fluctuations cannot be ascribed to speckle only but also to radiometric changes. The overall effect of the division by the "super-image" is the spatial stationarity improvement: ratio images are much more homogeneous than the original images. Therefore, filtering these ratio images with a speckle-reduction method is more effective, in terms of speckle suppression, than filtering the original multi-temporal stack. After denoising of the ratio image, the despeckled multi-temporal stack is obtained by multiplication with the "super-image". Results are presented and analyzed both on synthetic and real SAR data and show the interest of the proposed approach.

***Index Terms*—** Multi-temporal SAR series, ratio image, super-image, SAR, despeckling

1. INTRODUCTION

Synthetic aperture radar (SAR) imaging is a widely used remote sensing acquisition system due to its all time acquisition capability. However, the inherent speckle attached to any coherent imaging system affects the analysis and interpretation of SAR images. Therefore, a preliminary speckle reduction step is often proposed for a successful exploitation of SAR images. Plenty of denoising methods dedicated to the restoration of a single SAR image have been proposed in the past decades (see [1, 2] for a review). With the launch of recent radar satellites (Cosmo-SkyMed, TerraSAR-X, ALOS-2, Sentinel-1, etc.), more and more SAR images, with short revisit time or high resolution, are now available. Jointly processing several images of the same area can potentially provide better denoising results than the restoration of a single image. This is the path followed by several multi-temporal denoising methods such as 2SPPB [3] or MSAR-BM3D [4]. A drawback of such approaches is the increased computational complexity with longer time series. In this paper, we take a different approach by forming a summary of the multitemporal series through a "super-image" [5], and using this "super-image" to denoise the SAR image at a given date.

Here, we propose a ratio-based multitemporal denoising method which fully exploits the significant information of the multi-temporal stack through the "super-image". We consider multi-temporal images acquired on the same orbit, with similar incidence angles, and that have been accurately registered. The paper is organized as follows. In section 2, the general framework of the method called RABASAR (RAtio-BAsed multitemporal SAR despeckling) is described. Different methods to compute a "super-image" are discussed in section 3. Section 4 introduces the denoising of the ratio image. Section 5 presents experimental results of the method. Finally, some conclusions are drawn in section 6.

2. PRINCIPLE OF THE METHOD

Having huge multi-temporal stacks allows to produce an image with reduced noise thanks to temporal averaging (also called temporal multi-looking). In this paper we propose to exploit this "super-image" to build a ratio-based denoising framework (Fig.1). The proposed method is divided in 3 main steps.

First (step 1), a "super-image" is computed from the multi-temporal stack (serie of registered and calibrated SAR data). The average of the intensity images is the simplest way to compute a multi-look image and corresponds to the maximum likelihood estimation of the reflectivity if the temporal samples are i.i.d. (temporal fluctuations due to fully-developed speckle). In practice, different points have to be taken into account. First, since the data are temporally correlated and potentially changing in time, the noise reduction is spatially variable. Second, for changing areas, the mean

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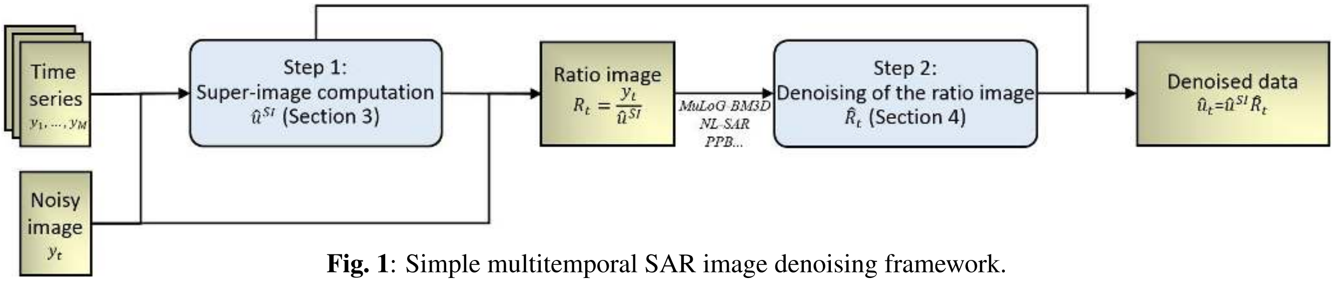


Fig. 1: Simple multitemporal SAR image denoising framework.

value has no physical meaning. Therefore, it can be interesting to introduce binary weights to average only similar data as done in [3]. These points will be discussed in section 3. This "super-image" is noted by $\hat{u}^{SI}$ in the following.

In the second step, starting from this "super-image", the ratio R_t between a noisy image y_t and the "super-image" should contain only the residual speckle noise and the temporal variations between the two images.

$$R_t = \frac{y_t}{\hat{u}^{SI}} \tag{1}$$

Then, this ratio is filtered to eliminate the noise fluctuations and keep only relevant information about the changes. In stable areas (where no change occurs other than speckle-related fluctuations), this ratio image is expected to be gamma distributed with mean 1 (i.e., independent of the radiometry at each pixel of the SAR image). The division in equation (1) therefore strongly increases the spatial stationarity (i.e., homogeneity) of the image. Any speckle filtering method can then be used for this step, as discussed in section 4.

In the last step, the original filtered image is recovered by simple multiplication of the denoised ratio and the "super-image". Experimental results on synthetic and real data are discussed in section 5.

3. "SUPER-IMAGE" OF A TEMPORAL STACK

The computation of a "super-image" from a multi-temporal stack can be done in different ways. Indeed, different means (arithmetic mean, geometric mean, Hölder mean) can be used, providing different kinds of information [5]. Besides, the changes between the dates can possibly be taken into account. In this paper we propose to use the arithmetic mean of intensity images, with the option of using binary weights to discard the intensity at some dates when a change occured.

3.1. Statistics of SAR images

Under Goodman's hypothesis, the fully developed intensity speckle is following a Gamma distribution:

$$\mathcal{G}[u, L](y) = \frac{L}{u\Gamma(L)} \left(\frac{Ly}{u}\right)^{L-1} e^{-\frac{Ly}{u}} \tag{2}$$

where L is the number of looks, y is the intensity value, u is the mean intensity related to the reflectivity of the scene. The intensity data can be written with a multiplicative noise model $y = uv$, with expectation $E[y] = u$ and variance $Var[y] = u^2/L$, where v follows a Gamma distribution $\mathcal{G}[1, L]$. With the increase of the number of looks L, the variance u^2/L decreases.

3.2. Arithmetic mean of a temporal stack

Given a series of M well registered SAR images indexed by time t, we now consider the intensity variables along the temporal domain. The arithmetic mean is defined by:

$$\hat{u}^{AM}(s) = \frac{1}{M} \sum_{t=1}^{M} y_t(s) \tag{3}$$

where s is the position in one image. If $y_t(s)$ is distributed according to Goodman's fully developed speckle model, with an underlying constant radiometry $u_t(s)$, then the arithmetic mean corresponds to the maximum likelihood estimator of $u_t(s)$. Because of the temporal coherence of SAR images in interferometric configuration, the resulting number of looks (ENL, Equivalent Number of Looks) may be less than the theoretical value, which is $L \times M$ under complete incoherence.

3.3. Binary weighted arithmetic mean

Changes may occur during the acquisition of the time series. In this case, the arithmetic mean is not reliable since it mixes different sample populations. To improve the computation of the reflectivity of the scene, we may focus on a specific image and select only the stable samples. To select these samples without being too much affected by speckle noise, a patch-based similarity criterion (using a generalized likelihood ratio test) proposed in [3] is used. This sample selection step, although improving the reflectivity estimation is time consuming since a patch-based comparison is done for each pixel in the multi-temporal stack.

3.4. Denoising the "super-image"

Because of varying coherence or unstable areas, or when using the binary weights, the "super-image" has a spatially varying ENL. This ENL is locally estimated [6] using a sliding window and a global ENL for the "super-image" is deduced by taking the maximum value. A global value is used to speed up the denoising process that is possibly applied on the "super-image".

Therefore, 4 “super-images” can be computed: arithmetic mean image (AM), binary weighted arithmetic mean image (BWAM) and their denoised versions.

4. RATIO IMAGE DENOISING

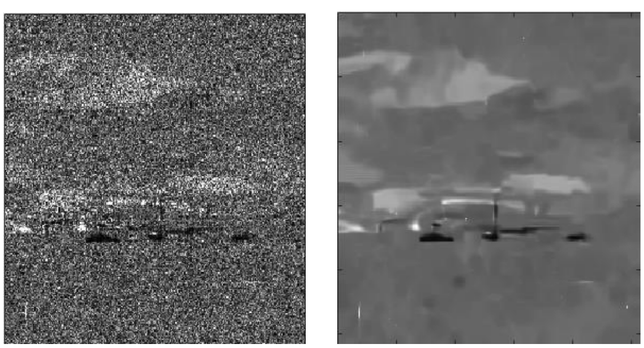
If $\hat{u}^{SI}$ is close to the noise free image u_t and intensity fluctuations follow the fully-developed speckle model, the ratio image R_t is distributed as a standard gamma distribution. When changes occur, the super-image $\hat{u}^{SI}$ does not completely normalizes the radiometry and speckle fluctuations have an average value that differs from 1. Nonetheless, the spatial homogeneity is largely improved in the ratio image compared to the original image.

Non-local methods offer a powerful approach to estimate the noise-free values $\hat{R}_t$, leading to smooth despeckled results while preserving edges and textures. For a given position s, similar positions i are searched within a window W_s centered at s. The similarities are computed based on patch comparisons. Then, the noise free value $\hat{R}_t(s)$ is estimated by the weighted average:

$$\hat{R}_t(s) = \sum_{i \in W_s} \omega(s,i) R_t(i) \tag{4}$$

where $\omega(s,i)$ is the weight of the i-th pixel in the estimation at pixel s, and weights are normalized ($\sum_{i \in W_s} \omega(s,i) = 1$).

This processing could benefit from any adaptive denoising method. In this paper, MuLoG-BM3D [7] is chosen to process the ratio image (Fig.2(b)). The resulting image is then $\hat{u}_t = \hat{u}^{SI} \hat{R}_t$.

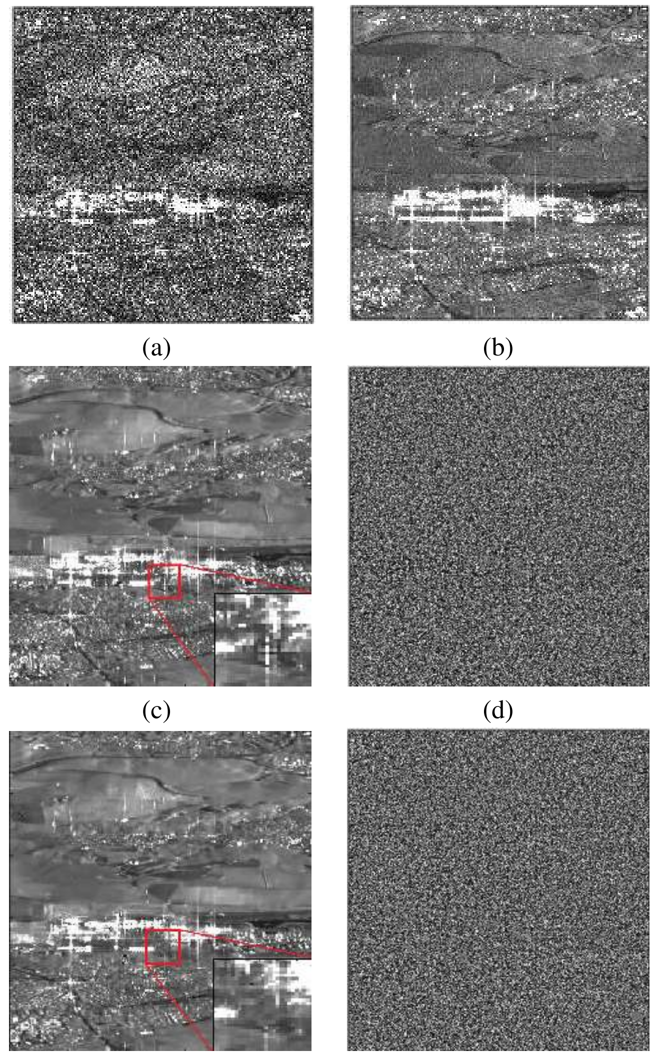


(a) (b)

Fig. 2: Sentinel-1 image over Paris area. (a)ratio image, (b)MuLoG-BM3D denoised result. Appearing (dark areas in (b)) and disappearing buildings are located in the middle of the image.

5. DENOISING RESULTS ANALYSIS

To evaluate the performances of the proposed method, different experiments have been conducted on simulated images and actual Sentinel-1 images. Two different multi-temporal denoising methods are also compared with 2SPPB [3] and MSAR-BM3D [4] methods. All the Sentinel-1 images are decorrelated by under-sampling by a factor 2, at the cost of spatial resolution reduction and are accurately registered using a sub-pixel image registration method.



(a) (b) (c) (d) (e) (f)

Fig. 3: (a)noisy Sentinel-1 data, (b)arithmetic mean image, (c)RABASAR denoised results with AM, (d)ratio between noisy data and result in (c), (e)RABASAR denoised results with BWAM, (f)ratio between noisy data and result in (e).

5.1. Using different “super-images”

As explained in the previous analysis, the “super-image” can be calculated in different ways. Two different “super-images” are used to evaluate the ratio-based denoising performances (Fig.3). All of them provide good filtering results, as can be observed by close inspection of the filtered ratio images.

When using the arithmetic mean to calculate the ratio, small areas with low values could be smoothed which leads to the apparition of new points in the denoised results (Fig.3(c) red rectangular). This phenomenon is obvious for the changes in the building areas. Using binary weighted arithmetic mean reduces the artifacts in these areas (Fig.3(e)). In addition, using binary weights for temporal averaging may lead to noisy areas in some changing part of the image.

5.2. Comparison with MSAR-BM3D and 2SPPB

To numerically evaluate the performances of these four different denoising methods, we produced simulated time series with changes from Sentinel-1 images (Fig.4). Different kinds of changes are introduced in the synthetic images: disappearing buildings, appearing buildings, forest areas and farmland areas. The changed values are extracted from the real Sentinel-1 SAR time series. We present results for the two different denoised "super-images" in this section.

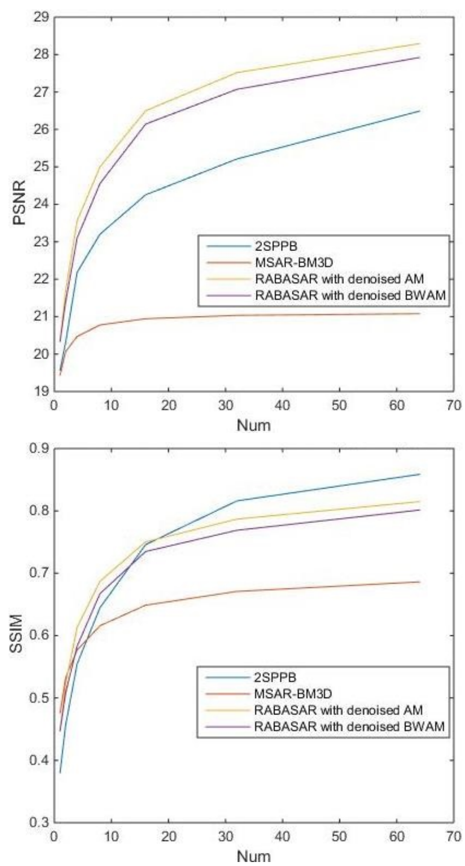


Fig. 4: PSNR and SSIM with different changed images. 64 synthetic Sentinel-1 images with changes are used.

Since MSAR-BM3D released code requires a number of time series equal to a power of 2, we only tested such cases, so as to keep the original performances of this method. Ratio-based denoising results always provide better PSNR than others. When using the denoised arithmetic mean image, RABASAR can provide better PSNR values than when using denoised binary weighted arithmetic mean image. With larger time series, RABASAR seems to obtain better denoising results. 2SPPB method results in less good PSNR and obtains better SSIM values when more than 16 images are used. However, 2SPPB acquired results have obvious bias in some farmland areas. MSAR-BM3D has been developed to keep the original behavior of bright points, so it gives smaller PSNR and SSIM.

6. CONCLUSION

This paper proposed a general framework for the reduction of speckle fluctuations in multi-temporal SAR images. It uses a "super-image" to exploit temporal information during the restoration of each SAR image. Standard single-image speckle reduction can be applied within this framework. The success of this simple approach comes from the improved spatial stationarity in the ratio images. The statistical hypotheses of the speckle reduction methods are more easily fulfilled with the ratio image than with the original images. Based on the processing of simulated time-series and actual Sentinel-1 stacks, a quantitative comparison with MSAR-BM3D and 2SPPB methods showed the potential of RABASAR to better preserve structures in multi-temporal SAR images while efficiently removing speckle. The "super-image" can be easily updated when new data become available so as to process new images on-line.

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