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A study of multitemporal filtering techniques for SAR images speckle reduction

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ABSTRACT: Our purpose is to study speckle filtering of multitemporal SAR images. This communication presents the results of the research undertaken in our laboratory. Different methods of quality restoration on amplitude SAR images are studied and different kinds of SAR multitemporal filters are proposed: the first one is based on a weighted average of each different acquisition. This filter is proposed by Stroobants and takes the temporal variation into consideration. It is simply based on a weighted average between the value of each temporal brother of a given pixel. The second describes two versions of the filter proposed by Quegan. In this case, the idea is to linearly combine M images from the same scene to produce M speckle reduced images. A linear intensity multitemporal filter based on the covariance matrix can combine images to achieve better speckle reduction, while preserving spatial resolution of individual channels. The covariance matrix plays an important role in this filter. When data are uncorrelated, the filter takes its simplest form. The last filter studied in this communication is based on the filter proposed by the team of Alparone.
The performance of these filters increases with the number of images used in filtering. The filtering effect can be quantified using ENLs measured from visually homogeneous regions in the images, bias and edge detection performance. A qualitative and quantitative comparison of all developed methods is achieved for four ERS-1 coregistered multitemporal SAR images of the Algerian region including urban areas of the town of Algiers. The encouraging results obtained, the improvements with respect to the classic algorithms of speckle filtering and the fundamental limits on filters performance are presented and discussed.

1 INTRODUCTION

Multitemporal SAR images are now a regular information source for many applications such as forest monitoring, land cover classification, change detection, etc. The speckle noise of SAR data makes operator photo-interpretation or automatic analysis more difficult than with optical or multi-spectral data. To overcome this difficulty, many applications use pre-filtering in order to reduce the speckle. The most straightforward strategy consists in applying classical bi-dimensional (2D) speckle filters image by image. The different 2D SAR image filtering techniques and their performance are well-known but they result in a trade--off between noise reduction and spatial resolution degradation.

The fusion of multitemporal SAR images offers a new opportunity to develop filters which benefit from the additional information brought by the temporal dimension. The behaviour of the so-called "multi-temporal filters" has to be carefully studied in order to be able to choose the most appropriate filter for a specific application.

This communication presents the results of the research undertaken in our laboratory. Different methods of quality restoration on amplitude SAR images are studied and different kinds of SAR multitemporal filters are proposed

2 METHODOLOGY

In order to achieve our objective, four multitemporal SAR images acquired by the ERS-1 satellite are co-registered in this data set.

This allows filter developers or end-users to apply SAR multitemporal filters on the data and to assess performance according to different kinds of criteria:

- statistical criteria based on image processing theory such as bias, equivalent number of looks, edge detection performance.
- operational criteria based on image photo-interpretation.

This data set can also be used to experiment fusion techniques dedicated to multitemporal images:

- change detection and analysis of time-varying features such as the coastline and flooded areas.
- permanent feature detection (such as roads, rivers...), which is often improved by the fusion of the redundant part of the information.

In our case, we studied and achieved some methods of multitemporal filtering presented in figure 1.

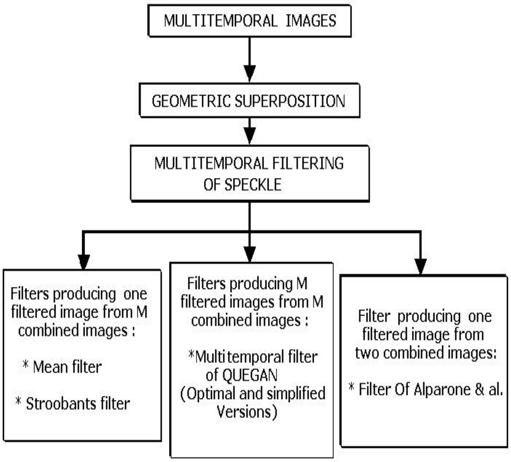

Figure 1. Presentation of the developed methodology

For the exploitation of the temporal set of the SAR data and before approaching the different methods of the multitemporal filtering of a speckle, a very precise geometric superposition stage is necessary.

2.1 *Average filter*

The principle of this filter is very simple, it consists in spatially averaging the different acquirements pixel by pixel according to the following equation:

$$J(i,j) = \frac{1}{M}\sum_{i=1}^{M} I_i(i,j) \tag{1}$$

Where: I_i, i = 1…., M, is the level of gray of the pixel to the position (i,j) of M pictures and J is the level of gray of the pixel to the position (i,j) of the filtered image.

From M combined images, we obtained only one image.

2.2 *Quegan filter*

2.2.1 *Optimal method*

This linear filter, proposed by Quegan and Le Toan (1998 and 2000), combines M images from the same scene in order to produce M speckle reduced images.

The general linear solution for producing a single image is given by the weighted sum:

$$J(i,j) = \sum_{i=1}^{M} A_i(i,j) I_i(i,j) \tag{2}$$

Where I_i , i = 1……, M, is the grey level at position (i,j) in channel i. the weighting coefficients are defined by the relation:

$$A \propto C_I^{-1}\sigma \tag{3}$$

where

$A^t = (A_1,....., A_M)$, $\sigma^t = (\sigma_1,......, \sigma_M)$ and C_I is the covariance matrix of the intensity data.

In all the expressions that follow, coordinates (i,j) are omitted.

Every filtered image J_K will depend of an A_{ki} coefficients:

$$J_k = \sum_{i=1}^{M} A_{ki} I_i \qquad k = 1,......., M \tag{4}$$

This temporal filter preserves the radiometric information according to the relation:

$$\langle J_k \rangle = \langle I_k \rangle = \mu_k \tag{5}$$

Where μ_k is the local mean of the pixel in the k^{th} image, so we can express it as follows:

$$\sum_{i=1}^{M} A_{ki} \langle I_i \rangle = \sum_{i=1}^{M} A_{ki} \mu_i = \mu_k \tag{6}$$

Therefore:

$$J_k - \langle J_k \rangle = \sum_{i=1}^{M} A_{ki} I_i - \sum_{i=1}^{M} A_{ki} \mu_i = \sum_{i=1}^{M} A_{ki} (I_i - \mu_i) \tag{7}$$

The variance of J_k (new pixel of the kth image) is given by:

$$\sigma_k = \sum_i \sum_j A_{ki} A_{kj} C_{ij}$$

Where C_{ij} is element ij of the covariance matrix, and it is calculated according the relation:

$$C_{ij} = \left\langle (I_i - \mu_i)(I_j - \mu_j) \right\rangle = \frac{\mu_i \mu_j}{\sqrt{L_i L_j}} \rho_{ij} \qquad (8)$$

Where L_i and L_j correspond to the equivalent number of looks (ENL) views in the images i and j respectively while ρ_{ij} is the interrelationship between them.

The coefficient A_{ki} is the main element of this filtering type since it minimises variance var (J_k), i.e. it minimises the speckle in the kth image. The determination of this coefficient requires the resolution of the equation:

$$\frac{\partial \left[V_k - \sum_{k=1}^{M} \lambda_k \left(\sum_{i=1}^{M} A_{ki} \mu_i - \mu_k \right) \right]}{\partial A_{ki}} = 0 \qquad (9)$$

The solution is given by resolving this equation.

The general approach of this filter can provoke mistakes on the ERS data, especially of essentially plant zones in the case of the cycle of 35 day repetition because it introduces the assessment of the temporal correlation between images (Quegan and al.,1998).

In this case the temporal interrelationship is supposed to decrease to very low values, with the exception of bare soils and urban zones.

2.2.2 *Simplified method*

The simplified version of the filter of Quegan is used in the case of images that are not correlated. In this case the matrix of covariance is diagonal, leading to a much simplified form of the filter. The equation of this filter is given by:

$$J_k = \frac{\mu_k}{M} \sum_{i=1}^{M} \frac{I_i}{\mu_i} \qquad (10)$$

Where M is the number of images, $\mathbf{J_k}$ is the filtered picture, $\mathbf{I_i}$ is the intensity and μ_i is the evaluation of the local mean of the rétrodiffusion coefficient. I_i, μ_i et μ_k are calculated for every position (i,j).

This temporal filter does not damage the spatial resolution. We have to specify that the two versions of the filter of Quegan (optimal and simplified methods) consist to combine M images linearly to produce filtered M images.

2.3 *Stroobants filter*

The approach presented here is proposed by Stroobants (Huot and al., 1998). The goal of a multidate based study is to enhance the radar image quality by reducing the speckle and we can also detect modifications occurring between two acquisition dates. The temporal repetitivity of a radar satellite is not sufficient to guarantee the ground stability and variations between two images which are not always due to the speckle.

This method takes these kinds of variation into consideration. It is based on a weighted average between the value of each temporal pixel situated in the same position of a given image:

Let I_s^i be the grey level of a pixel s on the k[th] acquisition and J_s^k the corresponding pixel after the filtering.

$$J_s^k = \mu_k \frac{\sum_{i=1}^{m} \alpha_i \frac{I_s^i}{\mu_i}}{\sum_{i=1}^{m} \alpha_i} \qquad (11)$$

μ_i corresponds to the local mean calculated on the pixel neighbourhood in the ith image. Its allows to keep the equality locally $J_s^k = I_s^k$. The weight coefficient α_i depends on the modifications between two successive images i and j. In order to quantify these modifications, three parameters are used:

* $A_{i,j}^s = \frac{\sigma_i}{\mu_i} = \frac{\sigma_j}{\mu_j}$ which measures the variation of the local texture;

* $B_{i,j}^s = \mu_i - \mu_j$ which measures the variation of the local mean;

* $C_{i,j}^s = 1 - |c|$ which measures the temporal stability of the structural patterns, linked to the correlation coefficient c.

$D_{i,j}^s$ is the linear combination of these last coefficients:

$$D_{i,j}^s = a\left|\frac{A_{i,j}^s - \mu_A}{\sigma_A}\right| + b\left|\frac{B_{i,j}^s - \mu_B}{\sigma_B}\right| + c\left|\frac{C_{i,j}^s - \mu_C}{\sigma_C}\right| \qquad (12)$$

a, b and c are set by the user. The first step of the processing is to find the correct threshold for $D_{i,j}^s$:

$$T_{\max} = \mu_D + d.\sigma_D$$

$$T_{\min} = \mu_D - e.\sigma_D$$

with d and e set by the user.

Then the following algorithm is used:

- If $D^s_{i,j} \geq T_{\max}$: It means that the current pixel is different from its temporal pixels of the same position, this information must be keeped $J^k_s = I^k_s$.
- If $D^s_{i,j} \leq T_{\min}$: the pixel is identical to its temporal pixels of the same position, J^k_s is the average of each I^i_s.
- If $T_{\max} \leq D^s_{i,j} \leq T_{\min}$: then J^k_s is given by the equation . α_i is inversely proportional to $D^s_{i,j}$, it follows the law illustrated in figure 2.

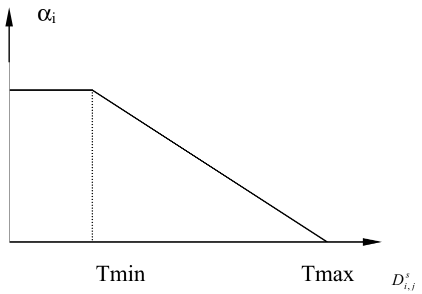

Figure 2. Determination of α value

This filter consists in combining M images to produce only one filtered image.

2.4 *Alparone filter*

In this survey a new algorithm to reduce the speckle is proposed by Alparone and al. (1999). It exploits the time correlation of two SAR images, taken with the same orbital parameters and incidence angles, and can be overlapped without any spatial registration.

A linear and reversible transformation is applied to two images in order to extract their common signal (redundant signal) and the change between them, while keeping properties of the multiplicative noise model.

The images are filtered in the transformed domain and are transformed therefore to give the filtered observations where the seasonal changes will be preserved.

The time correlation coefficient (TTC) of speckle is estimated (Alparone and al. 1999) for deriving the noise variance of the transformed data.

2.4.1 *Temporal transformation*

The temporal transformation is given by the pixel geometric mean and ratio of two overlapped images:

$$F_0(i,\ j) = \sqrt{f_0(i,\ j).f_1(i,\ j)}$$

$$F_1(i,\ j) = \frac{f_0(i,\ j)}{f_1(i,\ j)} \qquad (13)$$

Where $f_0(i, j)$ and $f_1(i, j)$ are the original images, while $F_0(i, j)$ and $F_1(i, j)$ the transformed ones.

The inverse transformation is given by :

$$f_0(i,j) = F_0(i,j).\sqrt{F_1(i,j)}$$

$$f_1(i,j) = \frac{F_0(i,j)}{\sqrt{F_1(i,j)}} \qquad (14)$$

The geometric mean strengthens the time-correlated component of the observed signal. It results in a signal to noise ratio that is higher than in each individual image and the difference removes the time-correlated signal component and highlights seasonal changes.

2.4.2 *Modelling of seasonal changes*

The radar cross-sections in two images are expressed as a signal common S(i,j) modulated by the square root of a change term C(i,j), and respectively by its reciprocal. Two terms of the speckle $u_0(i,j)$ and $u_1(i,j)$, having mean one, variance σ^2_u, and are correlated with each other with the coefficient of correlation CC ρ_{01}:

$$f_0(i,j) = S(i,j).\sqrt{C(i,j)}.u_0(i,j)$$

$$f_1(i,j) = \frac{S(i,j)}{\sqrt{C(i,j)}}.u_1(i,j) \qquad (15)$$

These equations define the temporal change model, analogous to the multiplicative model of the texture proposed by Ulaby and al. (1989). $F_0(i,j)$ and $F_1(i,j)$ can be written as follows :

$$F_1(i,j) = C(i,j)\,.\mu_R(i,j) \qquad (16)$$

$$F_0(i,j) = S(i,j)\,.\mu_G(i,j)$$

in which :

$$u_G(i,j) = \sqrt{u_0(i,j).u_1(i,j)}$$

$$u_R(i,j) = \frac{u_0(i,j)}{u_1(i,j)} \quad (17)$$

The variances of the noise $u_G(i, j)$ and $u_R(i, j)$ can be approximate by taking the first order developments of the root and of the ratio:

$$\sigma_G^2 = \frac{\sigma_u^2}{2}.(1+\rho_{01})$$

$$\sigma_R^2 = 2.\sigma_u^2.(1-\rho_{01}) \quad (18)$$

The value σ_G^2 is bigger than σ_R^2, depending on parameter ρ_{01}. While taking reports of relation squares given in equations 17 and 18, one will have then:

$$\rho_{01} = \frac{4\sigma_G^2 - \sigma_R^2}{4\sigma_G^2 + \sigma_R^2} \quad (19)$$

However, according to the equation 19, the coefficient ρ_{01} can be estimated from variances of noise terms in $F_0(i, j)$ and $F_1(i, j)$, that are respectively σ_G^2 and σ_R^2 .According to the model of change, ρ_{01} is independent of S(i,j), reflecting the average signal between the observations, whereas it will be found out to depend on the change term C(i, j).

2.4.3 *Filtering multitemporel of the speckle*

The local linear minimum mean square error (LLMMSE) (Kuan and al., 1985) estimates of S and C are given by:

$$\begin{cases} \hat{S}(i,j)=\bar{F}_0(i,j)+[F_0(i,j)-\bar{F}_0(i,j)]\times(1-\dfrac{\sigma_G^2.\bar{F}_0^2(i,j)}{\sigma_0^2(i,j)}).(\dfrac{1}{1+\sigma_G^2}) \\ \hat{C}(i,j)=\bar{F}_1(i,j)+[F_1(i,j)-\bar{F}_1(i,j)]\times(1-\dfrac{\sigma_R^2.\bar{F}_1^2(i,j)}{\sigma_1^2(i,j)}).(\dfrac{1}{1+\sigma_R^2}) \end{cases} \quad (20)$$

In which the pairs $\bar{F}_k(i,j)$ and $\sigma_k^2(i,j)$, k = 0,1, denote local average and the local variance of F_k, k=0,1.

The LLMMSE filter given by equations was devised in the assumption of white noise. When the speckle is spatially correlated, even though with same variance, the noise power measured on the local window is lower than when the noise is white. Hence, the filter is no longer adjusted to the actual SNR and becomes too strong. An empirical solution consists in defining an equivalent σ of the coloured speckle as:

$$\tilde{\sigma}_u = \sigma_u \sqrt{1-\rho_u}$$

In which ρ_u is the spatial CC of the noise affecting the data, which can be expressed as:

$$\rho_u \stackrel{\Delta}{=} \sqrt{\rho_x . \rho_y}$$

The TCC (time correlation coefficient) can be associated with high similarities of the vegetation cover which rules the surface scattering properties (Rignot & Van Zyl, 1993).

In our case, our work has been limited to the calculation and the assessment of the redundant signal given by the equation 20.

For the calculation of the values of variances σ_G^2 et σ_R^2 given by equations 17 and 18, the coefficient σ_u for the ERS data is equal to 0,302.

This filter consists in combining two pictures to produce filtered only one picture.

For our tests, four multitemporal SAR images on the region of Algiers acquired by satellite ERS-1 and coregistered. We present in the figures 3a – 8 the results obtained by the implemented filters.

3 DISCUSSION AND CONCLUSION

The goal of our study is to develop speckle multitemporal filters and to do different tests on the radar SAR images, in order to identify the most effective approach.

We can note according to figures 4 to 8 an improvement of the image quality. The average image gives a good reduction of the speckle but it smoothes edges and the texture very strongly, degrading the spatial resolution (figure 4).

The filter proposed by Stroobants allows an efficient filtering of the speckle on a small window of processing (figure 5), while preser ving structures as well as edges. However this filter is controlled by an important number of parameters which are not simple to fix.

The Quegan filter enables images from the same or different sensors, correlated or uncorrelated, to be jointly filtered. Because of the use of local weighting, spatial resolution is preserved in multi-channel filtered images. The filter can be greatly simplified by neglecting the correlation between images, producing similar results to those generated using an optimal multichannel filter. This is significant when there are correlations between many pairs of channels.

Figure 3a: Image of Algiers of 25 May 92

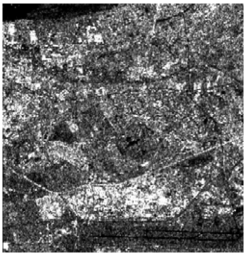

Figure 3b: Image of Algiers of 19 Aug. 92

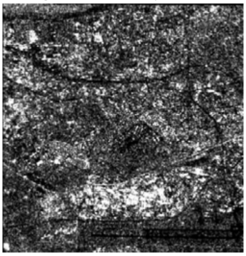

Figure 3c: Image of Algiers of 23 May 96

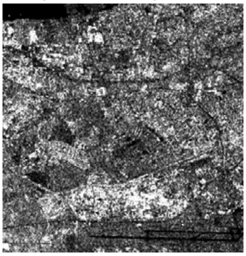

Figure 3d: Image of Algiers of 17 Aug. 96

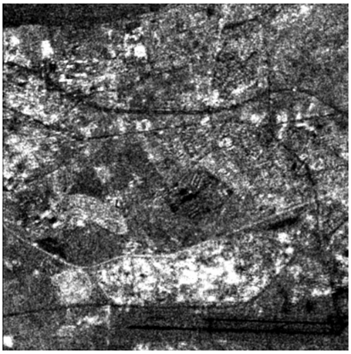

Figure 4: Image result of mean filtering

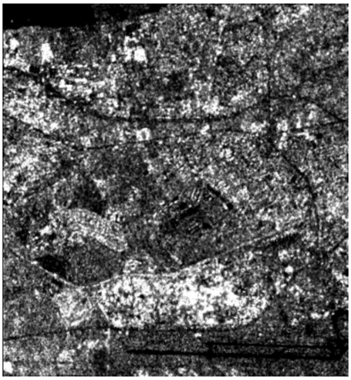

Figure 5: Image of Algiers filtering by Stroobants method with a 3×3 window

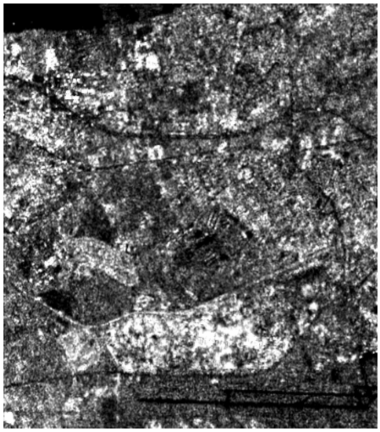

Figure 6: Image of Algiers of 17 Aug. 96 filtered by the Quegan optimal method with a 5×5 window

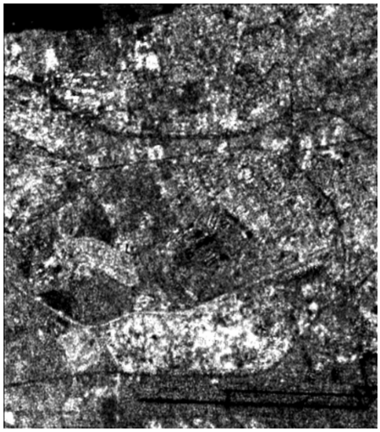

Figure 7: Image of Algiers of 17 Aug. 96 filtered by the Quegan simplified method

Figure 8: Images of Algiers of 17 Aug. 96 and 23/05/96 filtered by Alparone method with a 3×3 window

The images of the town of Algiers are partially decorrelated (great interval between dates of acquisition), this filter can introduce mistakes because it takes into account the correlation between images, however the simplified version of this filter is most suitable(figures 6 and 7).

The Alparone Filter is only conceived for two multitemporal images, the filtered image is shown in figures 8.

The quality of the filtered images of the town of Algiers is deteriorated because of the lack of correlation between the images.

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