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A comparative study on SAR images speckle reduction in a wavelet transform framework

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ABSTRACT: Speckle is a troublesome noise, disturbing radar SAR image interpretation and target classification. For reduction of speckle, numerous speckle filters have been proposed. Both suppression of speckle in a uniform area and preservation of edges have been pursued in these filters. In these years, the wavelet transformation is widely applied to images analysis, where the multi-resolution analysis by Mallat 1989) gives the theoretical basis. In this communication, we mainly study and compare two types of filters in a DWT framework: the ones based on the "à trous" algorithm of Dutilleux (1987), and those we develop using the "Mallat" algorithm (1989). For the first type, we apply either the Gaussian Gamma MAP and the Laplacian Gamma MAP filters to the wavelet coefficients got from the 'à trous' algorithm and we obtain the filtered image by the filtered images of the wavelet coefficients. For the second type, we use the "Mallat" algorithm with different wavelet bases instead of the "à trous" algorithm and we develop and discuss the case of Haar, Daubechies 4, 6, 8 and Biorthogonal (linear B-Spline and Battle Lemarie) Wavelets in two dimensions and show how they can be used for speckle reduction of SAR images.

1 INTRODUCTION

The speckle, appearing in synthetic aperture Radar (SAR) images as granular noise is due to the interference of waves reflected from many elementary scatters. This speckle in SAR images complicates the problem of image interpretation by reducing the effectiveness of image segmentation and classification; various ways have been devised to eliminate it.

The primary goal of the filtering ought to be reduction of the speckle noise without sacrifying the information content. The ideal speckle filter should adaptively smooth the speckle noise, retain the edge and the sharpness of the boundaries of the feature, and also preserve the subtle but distinguishable details, such as thin linear features and point targets.

We present in this paper a new method of speckle filtering based on the MAP approach which use multiresolution tool.

2 SPECKLE FILTRING TECHNIQUES

The speckle noise, which appears in SAR images, is generally modelled as a multiplicative noise:

$$g(i,j) = f(i,j).\,n(i,j) \qquad (1)$$

Where $g(i,j)$ is the intensity of an observed image pixel, $f(i,j)$ is the noise-free image pixel we wish to recover and $n(i,j)$ is the noise, characterized by a distribution with a unit mean (E[n]=1) and a standard deviation σ_n.

Much work has been carried out in the past concerning noise reduction. The most well known filters are adaptive filters based on the local statistics such as the Lee filter [3], Frost filter [4], and Kuan filter [5]. They reduce the speckle noise as a function of degree of heterogeneity measured by the local coefficient of variation. Hence refined algorithms have been proposed first by Lee [6] for the edge problem only. Edge denoising and preservation are performed by redefining the neighbourhood near the high contrast region.

Several ways to reduce speckle have been proposed [7] [8]. It has been accepted that some filters display superior performance over the others in smoothing speckle noise at homogeneous areas, while others display superior performance at the vicinity of edges.

3 THE MAP APPROACH FOR SAR IMAGES

The MAP estimate is obtained by maximizing the Bayes criterion with respect to R: I is the speckled intensity vector available in the actual SAR data; *R* is the radar reflectivity vector which is the quantity we want to restore. The Maximum A Posteriori (MAP) filtering method bases on the famous Bayes theorem:

$$P(R/I) = \frac{P(I/R).P(R)}{P(I)} \quad (2)$$

where P(R/I) corresponds to the PDF of the speckle which is a Gamma distribution. The MAP filter is calculated by the equation (3):

$$\mathrm{Log}[P(R/I)] = \mathrm{Log}[P(I/R)] - \mathrm{Log}[P(I)] + \mathrm{Log}[P(R)] \quad (3)$$

which gives the MAP estimate of R when $\log[P(I/R)]$ is maximum, then:

$$\frac{\partial}{\partial R}\mathrm{Log}[P(R/I)] + \frac{\partial}{\partial R}\mathrm{Log}[P(I)] = \frac{\partial}{\partial R}\mathrm{Log}[P(I/R)] + \frac{\partial}{\partial R}\mathrm{Log}[P(R)] \quad (4)$$

The filter equation becomes:

$$\frac{\partial}{\partial R}\mathrm{Log}[P(I/R)] + \frac{\partial}{\partial R}\mathrm{Log}[P(R)] = 0 \quad (5)$$

when $R = \hat{R}_{MAP}$.

3.1 *Gauss-Gamma map filter*

Assuming the Kuan hypothesis, the Gauss-Gamma MAP filter equation (5) is given by:

$$\frac{(R - E[R])}{\sigma_R^2} - L\left(\frac{I}{R^2} - \frac{1}{R}\right) = 0 \quad (6)$$

$$\hat{R}^3 - E[R]\hat{R}^2 + L\sigma_R^2(\hat{R} - I) = 0$$

and the MAP estimate of R is the solution of this equation by used a Newton iterative method. More realistic texture models are introduced by Lopes et *al*. [9] by replacing the Gaussian probability density function by a Gamma and a symmetrical Beta PDF's.

3.2 *Gamma-Gamma map filter*

Many authors have established that the detected intensity of scattering can well be represented by a K distribution. This situation is obtained when the coherent wave is scattered by a surface having a Gamma distributed. It is assumed that both the radar reflectivity and the speckle noise follow a gamma distribution. The radar reflectivity distribution *P(R)* is therefore described by:

$$P_\Gamma(R) = \frac{1}{\Gamma(\alpha)}\left(\frac{\alpha}{E[R]}\right)\exp\left(\frac{-\alpha R}{E[R]}\right)R^{\alpha-1} \quad (7)$$

where α represents the spatial heterogeneity parameter of radar reflectivity describing the texture of the scene, is given by:

$$\alpha = \frac{1}{C_R^2} \quad (8)$$

L represents the equivalent number of looks and C_R represent the local coefficient of variation of the scene, is given by:

$$C_R = \frac{\sigma_R}{E[R]} \quad (9)$$

The speckle distribution *P(I/R)* is given by:

$$P(I/R) = \left(\frac{L}{R}\right)^L \cdot \frac{1}{\Gamma(L)} . I^{L-1} . e^{-\frac{LI}{R}} \quad (10)$$

The Maximum a priori term is then equal to:

$$\frac{\partial}{\partial R}\log[P_\Gamma(R)] = \frac{\alpha - 1}{R} - \frac{\alpha}{\overline{R}} \quad (11)$$

The Gamma-Gamma MAP filter equation is given by:

$$\alpha\hat{R}^2 + (1 + L - \alpha)E[I].\hat{R} - L.I.E[I] = 0 \quad (12)$$

The MAP estimate of the radar cross-section for K distribution is given by:

$$\hat{R}_{MAP} = \frac{(\alpha - L - 1).E[I] + \sqrt{E[I]^2.(\alpha - L - 1)^2 + 4\alpha.L.I.E[I]}}{2\alpha} \quad (13)$$

The MAP estimate of R is a non linear combination of the observed intensity *I* and the local mean intensity *E[I],* where *I* is the value of the pixel to be corrected.

L. Gagnon (1999) were proposed an a modified version for the Gamma-Gamma filter, when α is equal to [10]:

$$\alpha = \frac{L + 1}{L.\left(\frac{\sigma_R}{E[R]}\right)^2 - 1} \quad (14)$$

3.3 *Beta-Gamma map filter*

With the Beta-Gamma Maximum a Posteriori (MAP) it is assumed that the radar reflectivity follows a Beta distribution, and the speckle noise follows a Gamma distribution. The Beta distribution is a positive distribution with 3 parameters: a scale parameter R_{max} and two parameters m and n. According to these last two parameters, the Beta distribution has great form diversity and can be used as a SAR image model or scene model [9]. In this paper we study the Beta symmetric role, when n=m. The radar reflectivity distribution *P(R)* is therefore described by:

$$P_{BS}(R)=\frac{\Gamma(2m)}{\Gamma^2(m)}\left(\frac{R}{R_{max}}\right)^{m-1}\left(1-\frac{R}{R_{max}}\right)^{m-1} \quad (15)$$

The Maximum a priori term is then equal to:

$$\frac{\partial}{\partial R}Log[P_{BS}(R)]=\frac{m-1}{R}-\frac{m-1}{R_{max}-R} \quad (16)$$

we are interesting to the case for n=m=1, so the Beta-Gamma MAP filter equation is given by:

$$\hat{R}^2(L-\alpha+3)+\hat{R}[(\alpha-2L+3).\bar{I}-LI]+2L.I.\bar{I}=0 \quad (17)$$

The MAP estimate of the radar reflectivity is given by:

$$\hat{R}_{MAP}=\frac{LI+\bar{I}.(2L-\alpha-3)-\sqrt{[LI-\bar{I}(2L-\alpha+3)]^2+2LI\bar{I}(2\alpha-6)}}{2(L-\alpha+3)} \quad (18)$$

4 MULTIRESOLUTION ANALYSIS AND WAVELETS

Let us define multi-resolution analysis of L^2 (R). It represents a sequence of closed subspaces $V_j \in L^2$ (R) satisfying the following properties:

a. $V_j \in V_{j+1}$.

b. $\overline{\bigcup_{j\in z} V_j} = L^2(R) \bigcap V_{j\in z} = \{0\}$.

c. $f(x)\in V_j - f(2x)\in V_{j+1}$.

d. $f(x)\in V_0 - f(x-k)\in V_0, k\in Z$.

e. There exists a scaling function, $\varphi\in V_0$ such that $\varphi(x-k)_{k\in z}$ is a basis of V_0.

It is clear from these proprieties, that the collection of function $\{\varphi_{j,k}\}_{k\in Z}$ defined as $\varphi_{j,k}(x)=2^{j/2}\varphi(2^j x-k)$, is a basis of V_j .The $\varphi_{j,k}$ functions, will be used to approximate the functions of $L^2(R)$. Since the union of all the V_j spaces is dense in L^2 (R).

Let us denote Wj a space complementing V_j in V_{j+1}, that satisfies $V_{j+1}=V_j \oplus W_j$, where $\oplus$ stands for direct sum. Consequently, we have $\oplus W_j=L^2$ (R). A function χ is a wavelet if the collection of functions $\{\chi(x-k)_{k\in Z}\}$ is a basis of W_0. The collection wavelet function $\{\chi_{j,k}\}_{k\in Z}$ defined as $\chi_{j,k}(x)=2^{j/2}\chi(2^j x-k)$ is a basis of $L^2(R)$.

The spaces W_j contains the "detail" information needed to go from an approximation at resolution j to an approximation at resolution j+1.

4.1 *Wavelets filter*

Details about the theoretical foundation of DWT can be found in numerous places. Here we will give a brief summary in terms of linear algebra and for a 1D signal. One can extend the description to images, similarly than Fourier transform, i.e. by processing rows and columns sequentially.

A one-level DWT of a vector $\vec{x}=(x_1,...x_n)$ (representing the N samplings of a 1D signal) is represented by a (generally complex) *N*x*N* block-circulant matrix *W*. The vector $\vec{w}$ of wavelet coefficients is then simply given by $\vec{w}=W.\vec{x}$. The inverse transform is represented by a matrix $\tilde{W}$ such that $\tilde{W}.W=I$.

If the transform is orthogonal, then $\tilde{W}=W^T$, otherwise the DWT is said to be bi-orthogonal. The fundamental block of *W* is a 2x*L* matrix *B* (*L*<*N*) where one row operates as a low-pass filter while the second is a high-pass filter. The elements of *B* depend on the bi-orthogonality and regularity conditions imposed to the wavelet basis. Half of the elements of $\vec{w}$ encodes the local details of $\vec{x}$ (the so-called wavelet coefficients) while the other half encodes the local tendencies. A multi-level DWT is computed via a pyramid algorithm where a half smaller matrix *W* operates on the "tendency" outputs of the previous level [10].

4.2 *Basic idea and algorithm*

The three detailed images in the subspace of the n-th level contain high spatial frequency information of the approximated image of the level (n-1)th level subspace. The detail images in the first level subspace contain high frequency information of the original image. The amplitude (the wavelet coefficient) of a pixel in the detail images takes a positive or negative value, and its expected mean is zero. The basic idea of the speckle reduction filter that we propose is:

Step 1. Decompose a SAR image into the wavelet subspace images with a pyramidal structure.

Step 2. Reduce the amplitude of each pixel in the detail images of each subspaces by applying a MAP filter in each subspaces.

Step 3. Reconstruct an output image from the modified subspaces images.

Our approach is to use the Mallat and the à trous [11] algorithm, like multiresolution tools.

4.3 *A trous algorithm*

The "à trous" is developed by Dutilleux (1987), it is used to realise a discrete "one-dimensional" wavelet transformation. It provides successive approximation of the original image with coarser and coarser resolution.

The difference of information between two successive approximations of a function f(x) is called wavelet coefficients, the wavelet coefficients are given by:

$$C_{j+1} = f_{j+1}(x) - f_j(x) \tag{19}$$

The original image can be reconstructed as follows:

$$f(x) = f_j(x) + \sum_{j=1}^{l} C_j(x) \tag{20}$$

For each resolution, the algorithm "à trous" produces single wavelet image coefficients. It has the propriety of complete reconstruction. However, this algorithm is neither an orthogonal nor a biorthogonal multiresolution analysis [12]. The application for this algorithm in the image, by using a low-pass filter given by:

$$\begin{pmatrix} \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \\ \frac{1}{8} & \frac{1}{4} & \frac{1}{8} \\ \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \end{pmatrix}$$

4.4 *Mallat algorithm*

a. Decomposition

Although also applying in the mono-dimensional case, the concept of the analysis multi-resolution described previously, was introduced by Mallat (1989) for an application to the image. To this goal, one introduces a function of separable two-dimensional scale defined by:

$$\varphi(x,y) = \varphi_{j,k}(x).\varphi_{j,k}(y) \tag{21}$$

when $\varphi_{j,k}(x)$ and $\varphi_{j,k}(y)$ are related respectively to scale applied in the direction "X", and the function of scale applied in the direction "Y". The orthogonal base of (V_j) is then given by:

$$\left[2^{-j}\varphi_{2^j}\left(x-2^{-j}n, y-2^{-j}m\right)\right]_{(m,n)\in Z^2} = \left[2^{-j}\varphi_{2^j}\left(x-2^{-j}n\right)\varphi_{2^j}\left(y-2^{-j}m\right)\right]_{(m,n)\in Z^2} \tag{22}$$

The discrete approximation of the signal $f(x,y)$ to the resolution 2^j is defined by:

$$A^d_{2^j} f = \left[\langle f(x,y), \varphi_{2^j}\left(x-2^{-j}n\right)\varphi_{2^j}\left(y-2^{-j}m\right)\rangle\right]_{(m,n)\in Z^2} \tag{23}$$

The expression of the difference in existing information between two successive approximations of the same image is carried out using three directional wavelets which are expressed in the form:

$$\psi^D(x,y) = \psi_{j,k}(x).\psi_{j,k}(y)$$
$$\psi^H(x,y) = \varphi_{j,k}(x).\psi_{j,k}(y) \tag{24}$$
$$\psi^V(x,y) = \psi_{j,k}(x).\varphi_{j,k}(y)$$

when ψ^D, ψ^H, ψ^V are respectively the wavelets allowing the calculation of the difference in information in the diagonal, horizontal and vertical directions. The signals of details to the resolution 2^j are given by:

$$D^H_{2^j} = \left[\langle f(x,y), \psi^H_{2^j}\left(x-2^{-j}n, y-2^{-j}m\right)\rangle\right]_{(m,n)\in Z^2}$$

(Vertical details)

$$D^V_{2^j} = \left[\langle f(x,y), \psi^V_{2^j}\left(x-2^{-j}n, y-2^{-j}m\right)\rangle\right]_{(m,n)\in Z^2}$$

(Horizontal details)

$$D^D_{2^j} = \left[\langle f(x,y), \psi^D_{2^j}\left(x-2^{-j}n, y-2^{-j}m\right)\rangle\right]_{(m,n)\in Z^2}$$

(Diagonal details)

As in the mono-dimensional case, the calculation of the successive approximations is carried out using the numerical filters. In the case of the image, the filters will be applied in lines then in columns.

b. Reconstruction

The reconstruction is done in a recursive way. One will thus reconstruct all the approximations through the axis of the resolutions by adding to the discrete approximation with the resolution 2^j the signals of the corresponding details.

4.5 *The distribution of wavelets coefficients*

The standardized histogram or, the function of density of probability (PDF) informs us about the distribution of the values of radiometry. Thus, in an original image, the PDF is in general multimode and difficult to model. The histogram of a sub image of coefficients of wavelets is unimodal and very pointed. That has a weak standard deviation, average null and a great number of coefficients of wavelets of low value. That can be modelled by a generalised Gaussian distribution (Antonini, 1991) defined by [13]:

$$P_{GG}(x) = \alpha.exp\left(-|\delta.x|^{\beta}\right) \tag{25}$$

With: $\alpha = \dfrac{\delta.\beta}{2\Gamma\left(\frac{1}{\beta}\right)}$ and $\delta = \dfrac{1}{\sigma}\sqrt{\dfrac{\Gamma\left(\frac{3}{\beta}\right)}{\Gamma\left(\frac{1}{\beta}\right)}}$

Where σ is a standard deviation of the modelled distribution.

In figure (1a) we present the distributions of the coefficients of wavelets, of a sub image of details deduced from the algorithm of a trous.

In figure (1.b, c, d) we present the distributions of the coefficients of wavelets, of each image of details deduced from the algorithm of Mallat (vertical details, diagonal details and horizontal details).

In figure (3)(e)-(h) we present the filtered images; (e) the proposed filter using the Haar basis, (f) the same using the D4 basis, (g) the same using the D6 basis, (h) the same using the D8 basis, and (i) the same using the Spline2 basis.

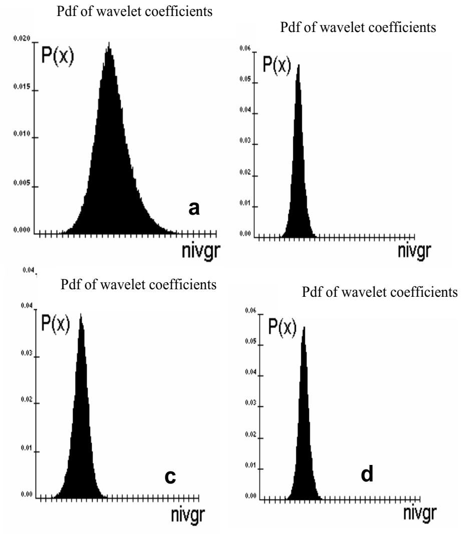


Figure 1. a) Practical wavelets coefficients image distribution deduced from the à trous algorithm; (b), (c), and (d) represent the three sub space images deduced from the Mallat algorithm.

4.6 *Description of the filter*

The proposed filter is based on the Bayesian approach, established under Gamma speckle model and the generalised Gaussian wavelets coefficients model. The models of distributions of the coefficients of wavelets (the scene) and speckle are:

- Distribution of the scene: $P(R) = \alpha.exp\left(-\left|\delta.R\right|^{\beta}\right)$
- Distribution of the speckle:

$$P(I/R) = \left(\frac{L}{R}\right)^{L} \frac{1}{\Gamma(L)} I^{L-1} exp\left(-\frac{L}{R}\right)$$

The Maximum A posteriori term is then equal to:

$$\frac{\partial}{\partial R} Log\left[P(R)\right] = -\beta.\delta^{\beta}.R^{\beta-1} \qquad (26)$$

The Maximum likelihood term of Probability is equal to:

$$\frac{\partial}{\partial R} Log\left[P(I/R)\right] = L.\left(\frac{I}{R^2} - \frac{1}{R}\right) \qquad (27)$$

The equation of filter MAP is given by:

$$\frac{\partial}{\partial R} Log\left[P(I/R)\right] + \frac{\partial}{\partial R} Log\left[P(R)\right] = 0 \qquad pourR = \hat{R}_{MAP} \quad (28)$$

By replacing the equations (26) and (27) in (28), which brings us to the general expression of the Gauss-Generalized-Gamma MAP filter which is:

$$R^{\beta+1} + \frac{L}{\beta.\delta^{\beta}} R - \frac{L}{\beta.\delta^{\beta}} I = 0 \qquad (29)$$

Two cases arise for the resolution of the general equation of the filter:

- First case for β=1:

In this case the distribution of the coefficients of wavelets approaches as well as possible with a Laplacian law. In this case the filter is known as **Laplace-Gamma MAP** and its equation becomes:

$$R^2 + \frac{1}{\delta} R - \frac{L}{\delta} I = 0 \qquad (30)$$

when $\delta = \frac{\sqrt{2}}{\sigma_I}$ I is the intensity of the pixel to treat image of coefficients of wavelets, σ_I is the standard deviation local in the image of coefficients of wavelets and L is the number of looks.

The equation (30) of the second degree admits a real solution ranging between the average *E[I]* and observed *I* is given by:

$$\hat{R}_{LG_{MAP}} = -\frac{L}{2\delta} + \frac{1}{2}\sqrt{\left(\frac{L}{\delta}\right)^2 + 4\left(\frac{L.I_c}{\delta}\right)} \qquad (31)$$

- Second case for β=2:

In this case the distribution of the coefficients of wavelets approaches as well as possible with a Gaussian law. In this case the filter is known as Gauss-Gamma MAP and its equation becomes:

$$R^3 + \frac{L}{2.\delta^2} R - \frac{L}{2.\delta^2} I = 0 \qquad (32)$$

The equation (32) admits a real solution ranging between the average *E[I]* and the observed *I*, that one will solve in an iterative way by the method of Newton.

$$\text{With: } \delta = \frac{\mathbf{0.7071}}{\sigma_I} \qquad (33)$$

The application of the filter implies the determination of two thresholds S_a and S_b.

Three cases arise, in the first case ($0 < \sigma_I \leq S_a$), one assigns the average value of the window of treatment the central pixel, which corresponds to low values of the standard deviation, the second case ($S_a < \sigma_I < S_b$), one applies the filter and in the last case ($\sigma_I \geq S_b$), one preserves the value of the pixel to be treated because it has a structure with strong diffusers. The choice of the values of the thresholds is carried out according to the following relation:

$$\begin{cases} S_a \cong \sigma \\ S_b \cong 2\sigma \end{cases} \quad (34)$$

When σ is the standard deviation of the image of coefficients of wavelets.

The expression of the filter, taking account of the thresholds, is rewritten in the following way:

$$\begin{cases} 0 < \sigma_I \leq S_a & \hat{R}_{MAP} = \bar{I} \\ S_a < \sigma_I < S_b & \text{The filter is operational} \\ \sigma_I \geq S_b & \hat{R}_{MAP} = I_c \end{cases} \quad (35)$$

5 COMPARISON CRITERIA

Two methods of evaluation are regularly used:

The first is the visual appreciation, which consists in checking the clearness of the image, as well as the safeguarding of edges and the structures. Figure (3) is a zoom produced on the image of Laghouat presented in figure (2). It makes it possible to visualize the effects of the various filters on the structures. Nevertheless, this method remains insufficient to characterize the effectiveness of a filter.

The second method is based on statistical criteria necessary to objectively quantify the quality of the filtered image; a set of criteria will be established to measure the retention of the mean value in homogeneous areas, the speckle reduction capability, edge sharpness, thin feature preservations and point target retention.

- *Speckle reduction*

In homogeneous areas, the equivalent number of looks (ENL) is also frequently used to measure the amount of speckle reduction. The ENL for amplitude SAR images is defined as:

$$ENL = \left(\frac{0.522}{C_A} \right)^2 \quad (36)$$

- *Radiometry preservation*

This parameter makes it possible to evaluate the skew of estimate of average radiometry on a broad homogeneous zone introduced by filtering. It is calculated in decibels (dB) by:

$$Bias\ (dB) = 10\ Log \left(\frac{\mu_{IF}}{\mu_I} \right) \quad (37)$$

When μ_I and μ_{IF} indicate respectively average radiometry of a homogeneous zone estimated respectively in the original image and the filtered image.

6 APPLICATION AND RESULTS

The generalised Gaussian Gamma filter has been applied on an ERS-1 SAR image corresponding to an area of southern Algeria called Laghouat. The filter proposed is compared with other known filters (Gauss Gamma MAP, Gamma Gamma MAP…etc). The results are reported in table 1. Table 1 gives the comparison ENL and Bias for various filters, using an original 3-looks image.

Table 1: Comparison of speckle reduction

Image	Mean	CI	ENL	Bias(dB)
Original	**81.712**	**0.286**	**3.348**	0
Gauss-Gamma MAP	**81.901**	0.160	10.68	**0.023**
Gamma-Gamma MAP	79.842	0.159	10.82	-0.232
Beta-Gamma MAP	80.958	0.157	10.85	-0.093
Modified Gamma-Gamma MAP	80.219	0.153	11.61	-0.184
Gauss-Gamma with				
Haar	**81.967**	0.218	5.756	**0.0311**
Daubechies4	81.262	0.227	5.298	-0.0551
Daubechies6	80.708	0.218	5.758	0.0117
Daubechies8	81.766	0.221	5.585	0.0066
Spline2	80.880	**0.212**	**6.049**	-0.1024
Laplace-Gamma using the "a trous" algorithm	80.494	0.221	5.621	-0.1502
Gauss-Gamma using the "a trous" algorithm	**81.346**	**0.216**	**5.866**	**-0.0449**

7 CONCLUSION

In this study we developed a new filter called Gaussian Generalised Gamma filter which is applied to SAR images. We noted that the filter smoothes the speckle noise at the homogeneous areas and vicinity of edges, but also it preserves the structural information such as edges between areas, curvilinear structures like roads, and point targets.

The results obtained by the whole of the methods tested on SAR real images show that the filters Gauss-Gamma MAP and Laplace-Gamma MAP based on the wavelet transform seem to give better results compared to the other filters recognized as powerful for the reduction of the multiplicative noise in the image radar. Its two filters combine the two characteristics of a method of filtering with knowing the capacity of smoothing and preserving of the structures. It should be noted that the results obtained by using the algorithm of Mallat as a tool for decomposition in wavelet, are worse than those obtained with the "a trous" algorithm.

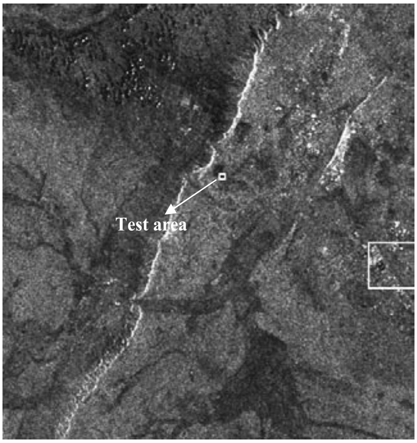
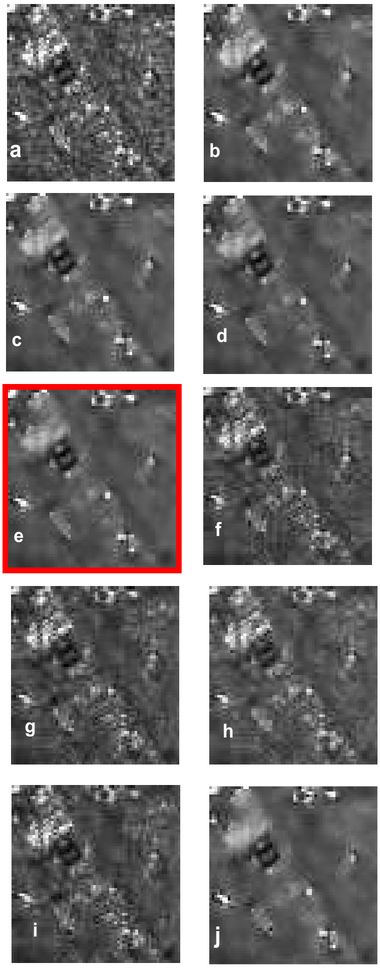


Figure.2: original image of Laghouat region



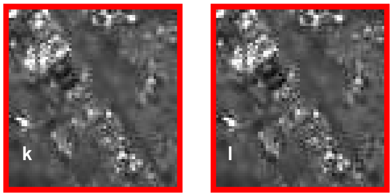


Figure.3: A zoom on structures on the image of Laghouat: a) Original image, b)Gauss-Gamma filter, c) Beta-Gamma filter, d) Gamma-Gamma filter, e) modified Gamma-Gamma filter, f) Gauss-Gamma (Haar), g) Daubechies_6, h) Daubechies_8, i)Spline_2, j) Daubechies_4 k) Laplace-Gamma filter (using à trous), l) Gauss-Gamma (using à trous).

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