SPECKLE REDUCTION WITH EDGE-PRESERVING

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ABSTRACT

Coherent imagery emerges as one of the major domains in image processing and includes topics as diversified as radar, medical and surface analysis. Whatever the application, the resulting image is noisy corrupted. In coherent imaging, images suffer from speckle noise [1], whose main characteristic is to be multiplicative.
The proposed method takes explicitly into account the multiplicative property of the noise while preserving discontinuities in the restored image. Moreover, in a second step our algorithm estimates the noise, thus the information contained in the speckle still remains usable.

1. INTRODUCTION

Well known methods for reducing speckle are homomorphic filtering [3] where the multiplicative nature of the noise suggests a logarithmic tranformation in order to get an additive noise. By the way, we can use classical methods such as Wiener filtering and Tikhonov regularization. This method presents two main drawbacks. First, numerical difficulties arise for values near zero. Second, the probability density function (pdf) of the transformed signal is no more gaussian, even though most of the classical filtering technics are optimal for gaussian distributions.
Another approach consists in multiscale processing (for example wavelets tranform [2]) to reduce noise concentrated in some subimages. The multiplicative aspect of the noise is neglected in all these methods.
In this paper we proposed a new algorithm wich take into account this aspect, in order to improve the image estimation. In actual fact, we alternatively estimate both image and noise.The enhancement is shown from the numerical and experimental results.

2. MODEL

Let us state the following multiplicative model:

$$Y = X_d.B = B_d.X \qquad (1)$$

with :

$$X_d = diag(X) \quad and \quad B_d = diag(B)$$

Y represents the magnitude of the observed image, X the image and B a multiplicative noise.

In image processing, the knowledge of the mesured data and the model is not sufficient to determine a satisfying solution (ill-posed problem). It is necessary to impose constraints on the solution. Then we assume as *a priori* that the noise intensity follows a Gamma pdf, and is independant and identically distributed over all the image.

Since variable are modulus images, we can assume that :

$$\forall i \in [1..n] \quad \begin{cases} y_i > 0 \\ x_i > 0 \\ b_i > 0 \end{cases} \qquad (2)$$

The problem now is to estimate both image and noise.

3. ESTIMATION OF BOTH IMAGE AND NOISE

To introduce an *a priori* on image X, a Markov Random Field (MRF) is assumed with the Gibbs density function. The potential function (φ) applied on the gradient of the image (∇X) is choosen in order to preserved edges. The Maximum *A Posteriori* (MAP) estimate is given by the criterion :

$$J(X,B) = J_1(X,B) + \lambda_g^2 J_2(X) \qquad (3)$$

where

- $J_1(X, B) = \|Y - B_d X\|^2 = \|Y - X_d B\|^2$ represents the data term

- $J_2(X) = \sum_{ij} \left[\varphi \left(\frac{x_{i+1,j} - x_{i,j}}{\delta} \right) + \varphi \left(\frac{x_{i,j+1} - x_{i,j}}{\delta} \right) \right]$ represents the regularization term where φ is the potential function and δ a threshold level from which we decide to preserve or to smooth the edges [4]. The φ function must satisfy some properties which can in particular be found in [5].

Moreover, the noise intensity is distributed according to a Gamma pdf. And, the i-th component b_i of B has as probability density function (for a normalized L-look multiplicative fading process [7]) :

$$p(b_i) = K \frac{b_i^{2L-1}}{\sigma^{2L}} exp \left[-\frac{b_i^2}{2\sigma^2} \right] \qquad (4)$$

with

$$K = \frac{1}{2^{L-1}\Gamma(L)} \qquad (5)$$

where we infer the law of B:

$$p(B) = \prod_i K \frac{b_i^{2L-1}}{\sigma^{2L}} exp \left[-\frac{b_i^2}{2\sigma^2} \right] \qquad (6)$$

Maximizing this probability leads to minimizing the log-likelyhood:

$$J_3(B) = -ln[p(B)] = -\sum_i ln \left(K \frac{b_i^{2L-1}}{\sigma^{2L}} exp \left[-\frac{b_i^2}{2\sigma^2} \right] \right) \qquad (7)$$

Thus, we propose to minimize the following criterion:

$$J(X, B) = J_1(X, B) + \lambda_g^2 J_2(X) + \lambda_b^2 J_3(B) \qquad (8)$$

4. ALGORITHM

The following alternate minimization of J is proposed to compute a solution :

- When B is fixed, the new estimate of X is given by solving $\frac{\partial J(X,B)}{\partial X} = 0$ which yield to the linear equation [4]:

$$\left(B_d^t B_d + \frac{\lambda_g^2}{\delta^2} \Delta_{pond} \right) X = B_d^t Y \qquad (9)$$

with Δ_{pond}, a discrete approximation of a weighted laplacian. At site (i,j), the coefficients are given by :

$$\begin{pmatrix} 0 & \lambda^N & 0 \\ \lambda^W & 0 & \lambda^E \\ 0 & \lambda^S & 0 \end{pmatrix}$$

The weights are defined as follow:

$$\lambda^W = \frac{\varphi'(x_{i,j-1} - x_{i,j})}{2|x_{i,j-1} - x_{i,j}|} \qquad \lambda^E = \frac{\varphi'(x_{i,j+1} - x_{i,j})}{2|x_{i,j+1} - x_{i,j}|}$$

$$\lambda^S = \frac{\varphi'(x_{i+1,j} - x_{i,j})}{2|x_{i+1,j} - x_{i,j}|} \qquad \lambda^N = \frac{\varphi'(x_{i-1,j} - x_{i,j})}{2|x_{i-1,j} - x_{i,j}|}$$
$$(10)$$

- When X is fixed, we compute the new image's estimate derivating the criterion $J(X, B)$ with respect to B. Thus we obtain the normal equation:

$$\left(X_d^t X_d + \frac{\lambda_b^2}{2\sigma^2} I \right) B = X_d^t Y + (2L - 1)\frac{\lambda_b^2}{2} B^{-1} \qquad (11)$$

with $\quad B^{-1} = (\frac{1}{b_1}, .., \frac{1}{b_i}, .., \frac{1}{b_n})^t$

Note that each b_i is solution of a second order equation, given by the positive value (2).

We propose the following algorithm:

B^0 = Noise's initial guess
X^0 = Image's initial guess

Repeat
    Compute new estimate X^{n+1} solving (9)
    Compute new estimate B^{n+1} solving (11)
Until convergence

5. EXPERIMENTAL RESULTS

The experimentation of this algorithm was processed both on a 64x64 pixels synthetic data, and on a real SAR image (3-look).

First, on a 64x64 pixels synthetic phantom derived from Shepp & Logan's phantom (1-look). The potential function used is the Green's function [9] $\varphi_{GR}(u) = log[cosh(u)]$ and the regularizing parameters are $\lambda_g = 2.3$, $\delta = 1$ and $\lambda_b = 0.75$.
The results (figures 1, 2, 3) presented are the original image, the noisy image, the regularized image, the noise's estimate image and a cross section of the three firsts image at the 27-th line.

Secondly, on a real ERS-1(©ESA) SAR[1] image (3-look) of Saragosse (Spain). The potential function used is the Green's function [9] and the regularizing parameters are $\lambda_g = 50$, $\delta = 1$ and $\lambda_b = 25$.

The results (figures 4, 5, 6, 7, 8, 9) presented are the original 3-look modulus image, the restored image, the edges image and the histogram plots.

6. CONCLUSION

We observe a good restoration of the image with a significant noise reduction. The noise estimation is accurate on the flat areas, while on the egdes, it strongly depends on the model of the discontinuities.

Future works concern the improvement of our edges model, by taking strongly into account the *a priori* on the noise, for example mean and variance.

7. REFERENCES

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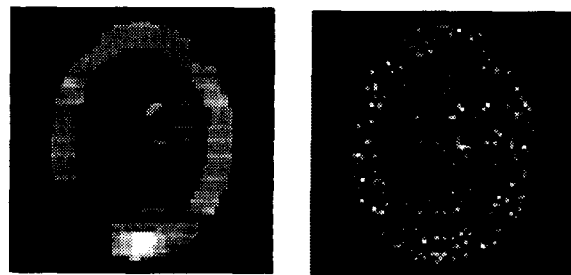Figure 1: (a) Original image.   (b) Noisy Image.
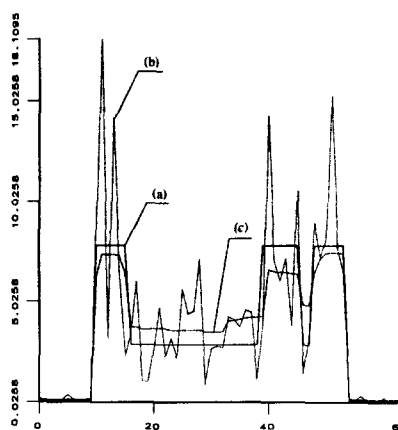

Figure 2: (a) Restored image.   (b)Noise estimate.

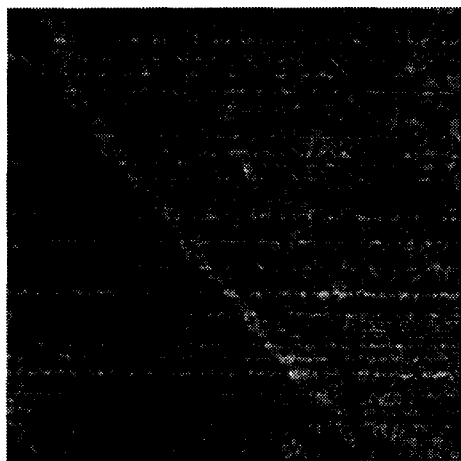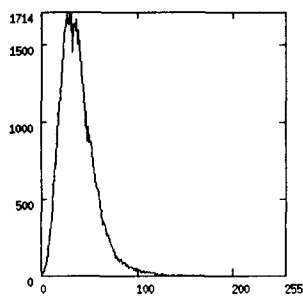Figure 3: (a): Original; (b): Noisy; (c): Restored.

Figure 4: Original image.

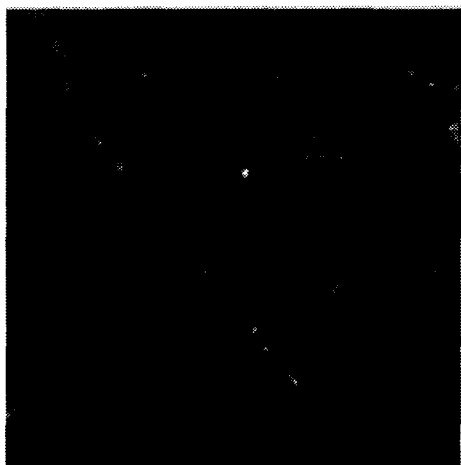Figure 7: Original image histogram.
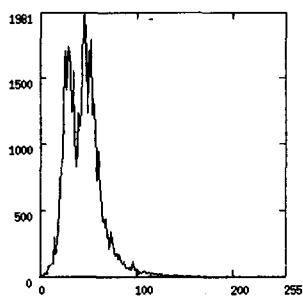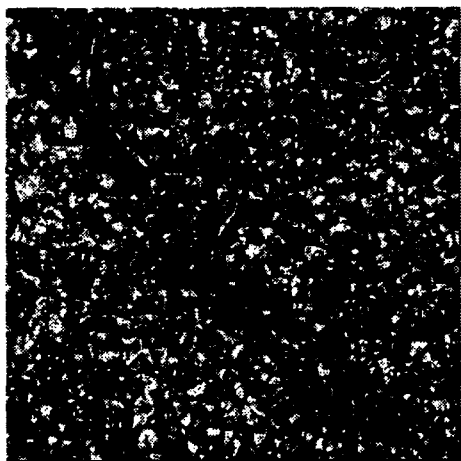

Figure 5: Restored image.
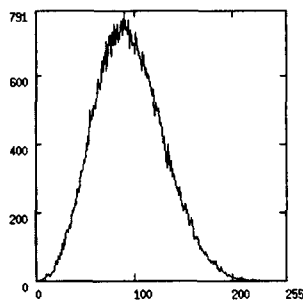

Figure 8: Restored image histogram.

Figure 6: Edges image.

Figure 9: Estimated noise histogram.