An Adaptive Total Variation method for Speckle reduction in Medical Ultrasound Imaging

Meriem Hacini, Fella Hachouf
Electronic Department
Automatic and Robotic Laboratory, Constantine University
Ain el Bey Road, 25000 Constantine, Algeria
meriem.hacini@yahoo.fr, fhachouf@wissal.dz

Khalifa DJEMAL
Laboratoire Systmes Complexes
Universit d'Evry Val d'Essonnes 40 Rue du Pelvoux,
91020 EVRY Courcouronnes Cedex, France
djemal@iup.univ-evry.fr

***Abstract*—To reduce the speckle noise and preserve the edge information, a novel algorithm based on an adaptive total variation method is proposed. The smoothing process uses adaptive windows whose shapes, sizes and orientations vary with image structures. Adaptive window calculate instantaneous Lagrange coefficient for edge areas with more accuracy avoiding smoothing these regions and performing well in large ones. Experimental results show that, the performance of the proposed method is satisfactory in terms of both speckle suppression and preservation of medical ultrasound image details.**

***Index Terms*—Image Smoothing, Adaptive Window, Total Variation, Speckle Suppression, Medical Ultrasound Image.**

I. Introduction

Ultrasonic image quality is often degraded by the speckle noise [1]. Speckle results directly from the use of a coherent transducer and occurs when the structure in the object is on a scale too small to be resolved by the imaging system. It is an interference phenomenon - small scatterers cause constructive and destructive phase interference at the receiving array. Speckle is an undesirable property since it can mask small but significant features and hence reduces the ability of human observer to discriminate fine details in diagnostic examination. It also decreases the efficiency of further image processing such as edge detection.

Various speckle reduction methods have been reported in the literature. Popular methods include the Lee method [2], the Kuan method [3], Speckle- reducing anisotropic diffusion SRAD [4,5,6], variational methods [6,7,8]. These methods offer good performance for various speckle levels. However, the contours are often deteriorated. Ultrasound image have some special features that must be preserved by the filtering, such as bright large scale interfaces between organs, structures with dimensions comparable to speckle size, and boundaries between two regions with slightly different gray levels. Therefore, linear nonadaptive smoothing techniques used for other image processing purpose may not be adequate for ultrasound images. Many of such techniques introduce severe blurring and show unacceptable performances in speckle elimination. Various adaptive image smoothing methods have been developed throughout years with early reviews provided by [9-13]. Recently, Liu et al [14] proposed a speckle reduction by adaptive window anisotropic diffusion algorithm which calculates the instantaneous coefficient of variation using various orientations and windows sizes that can locally adapt to the image structure. In this work, to provide an improvement to the edge-preserving methods, an extension of the Minimized Total Variation (MTV) method presented in [8] is adopted; the Minimized Total Variation-Adaptive Window MTV-AW. The proposed method consists of computing appropriately instantaneous Lagrange multiplier of the variational equation, using shaped, sized and oriented locally filtering windows. Each window can locally match to the image structure. Performance of the filter is tested on both synthetic and breast cancer images. The results are presented in a comparative way with the MTV proposed in [8].

In the next section, the adaptive speckle suppression including instantaneous Lagrange multiplier measurement and filtering procedure, are presented. Section III, covers simulation results and comparison. Conclusion and future work are drawn in Section IV.

II. THE ADAPTIVE SPECKLE SUPPRESSION METHOD

An ultrasound image containing speckle noise has been modeled by Loupas et al [14] as follows:

$$g(x,y) = f(x,y) + \sqrt{f(x,y)}.b(x,y) \tag{1}$$

Where f is the clear image and g the observed image. The image $b(x,y)$ is a multiplicative noise considered as Gaussian centered with standard deviation σ_b. $\sqrt{f(x,y)}.b(x,y)$ term models the ultrasound noise images [11, 12].
We define the two following constraints:

$$\begin{cases} \int_\Omega (f(x,y) - g(x,y))dxdy = 0 \\ \qquad\qquad\qquad\qquad and \\ \int_\Omega (\frac{f(x,y)-g(x,y)}{\sqrt{f_x^2+f_y^2}})^2 dxdy = \sigma_b^2 \end{cases} \tag{2}$$

Using Euler-Lagrange equation under (2) and considering the numeric resolution based on the gradient method [6], Evolution process is controlled by the time t. In these conditions, we obtain the following equation

$$\frac{\partial f^{(t)}}{\partial t} = \frac{\partial}{\partial x}\left(\frac{f_x^{(t)}}{\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}}\right) + \frac{\partial}{\partial y}\left(\frac{f_y^{(t)}}{\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}}\right) + \lambda^{(t)}(1 - g^2/{f^{(t)}}^2) \tag{3}$$

Where $\lambda^{(t)}$ is the Lagrange multiplier, depending on the evolution parameter t. The neighborhood window is important for calculating the Lagrange multiplier of an image. The literature shows that the estimation of Lagrange multiplier remains a delicate point and is directly related to the filter's performance. Here, we analyze the impact of the instantaneous Lagrange multiplier which is based on the resolution of non linear PDE equation using the method of Rudin et al [6]. The Lagrange multiplier is given by [8]:

$$\lambda^{(t)} = -\frac{1}{K(t)}\int_\Omega \left(\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}\right) - \left(\frac{g_x.f_x^{(t)} + g_y.f_y^{(t)}}{\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}}\right)dxdy \tag{4}$$

Where $f_x = \frac{\partial f}{\partial x}$, $f_y = \frac{\partial f}{\partial y}$ and

$$K^{(t)} = \sigma_b^2 + \int_\Omega \frac{(f^{(t)} - g)^2}{(f^{(t)})^2} \tag{5}$$

Eq. (3) is chosen to satisfy $\lambda^{(t)} \longmapsto 0$ when $K^{(t)} \longmapsto \infty$ so that the smoothing stops at the edges. When $K^{(t)} \longmapsto \int_\Omega(\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}) - (\frac{g_x.f_x^{(t)} + g_y.f_y^{(t)}}{\sqrt{(f_x^{(t)})^2 + (f_y^{(t)})^2}})dxdy = K_0$ and $\lambda^{(t)} \longmapsto 1$ the eq. (3) should be a smooth filter in the homogeneous regions. In this way the process will mainly take place at the interior of the regions and it will affect the region boundaries. From equations given above, we can see that the value of $K^{(t)}$ decides whether or not the smoothing process is in the homogeneous area, which is dependent on the window size.

Near an object boundary, gradient magnitude in the direction normal to the boundary may be high, gradient magnitude in the direction along the boundary will be low, therefore, the window used to locate λ should be long side and aligns with the boundary, this operation prevents information on the two sides of the boundary and keeps the object boundary sharp. Thus, the window size is crucial for effective speckle suppression.

To maintain image structure while reducing noise, windows whose sizes, shapes, and orientations change with local image structure are proposed. This idea is illustrated in Fig 1. Instead of using square windows, rectangular windows whose dimensions and orientations adapt to local image details are used. Near a region boundary, the rectangular windows decreases and aligns with the boundary. In a homogeneous area, the windows will be enlarged, which implies the width W and high H of the window are related to the minimum and maximum gradient magnitudes at a pixel according to:

$$W = \frac{a}{(g_n + 1)} \tag{6}$$

$$H = \frac{a}{(g_m + 1)} \tag{7}$$

Where g_n and g_m are the minimum and the maximum gradient magnitudes at the pixel. The addition of 1 in the denominator is to avoid division by zero. The parameter a is the proportionality term. When $g_n = g_m = 0$, a can be considered the length of the side of the square window needed to smooth homogeneous areas in an image. It is obvious that a larger a should be selected for a noisy image. After that, the Lagrange multiplier λ is computed. If the window is rectangular, the pixels will be easy to locate. However, if the window is obliquely shaped, we need to perform rotation and translation operations to locate the pixels in the window.

Assuming that the window's center is located at the origin (0,0), after rotation by α_i and translation by (x_i, y_i), each pixel's coordinate position in the oblique window is given by the following equations:

$$x = W.cos(\alpha_i) - H.sin(\alpha_i) + x_i \tag{8}$$

$$y = W.sin(\alpha_i) + H.cos(\alpha_i) + y_i \tag{9}$$

(x_i, y_i) represents the current processing pixel's coordinate position, α_i the oblique angle is equal to $pi/2 + \theta$, θ the direction of maximum directional derivative at (x_i, y_i).

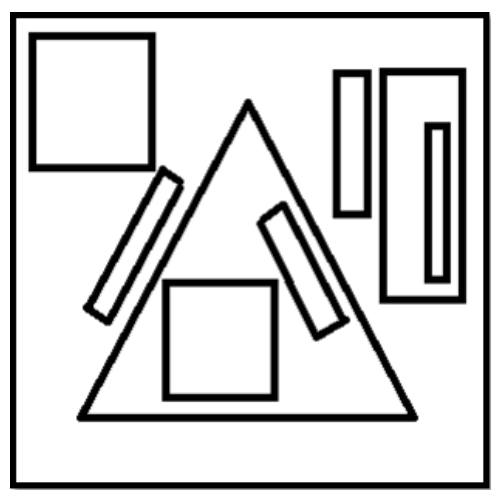

Fig. 1. Adaptive window used in the proposed MTV-AW method: in homogeneous areas, the window becomes large; while in edges areas the window becomes narrow and aligns in the edge direction

III. EXPERIMENTAL RESULTS AND DISCUSSION

To determine the efficiency of the proposed method, experiments were carried out using a computer simulated and real images. Fig. 2a shows a computer simulated image with different speckle noise level,lesion (the bright one) and cyst

(the dark one). The smoothing result of the proposed MTV-AW method for $a = 13$ pixels is shown in Fig. 2c.. The lesion and the cyst are preserved and different structures present in the image are detected. In Fig. 2b and Fig.2d, edges are computed using canny detector. The experiments values are adjusted after few tests. Fig. 3a shows a cardiac angiography image. The

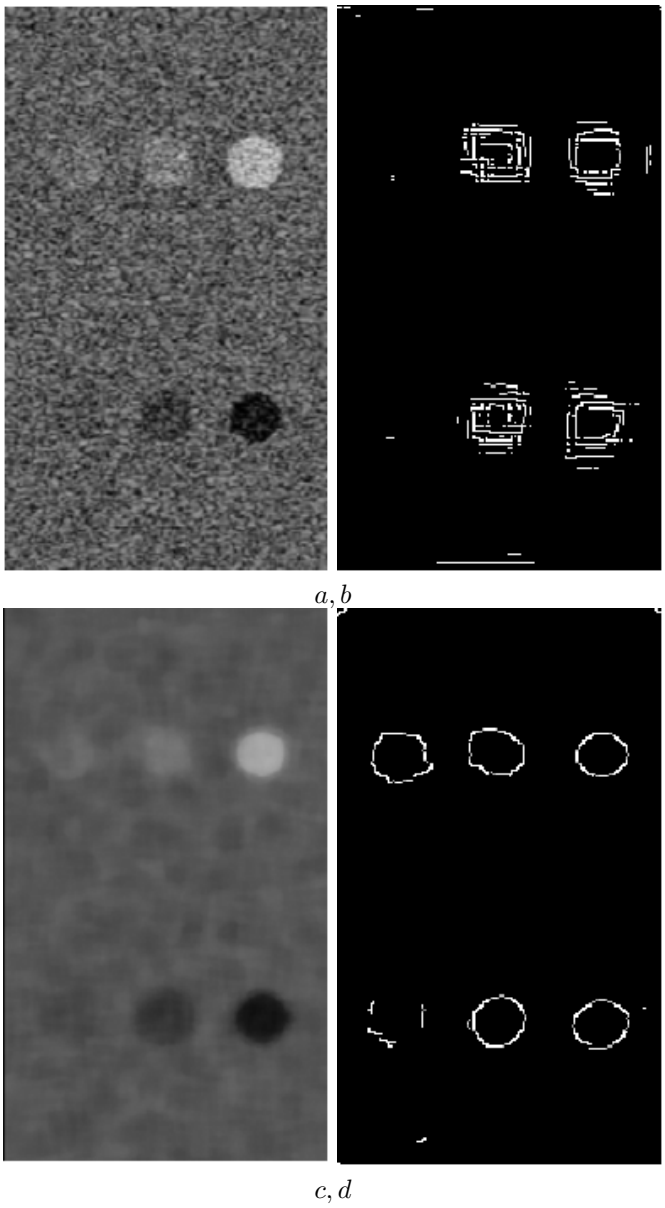

Fig. 2. The computer simulated image. a: The input image, d: The edge map of the input image, $\sigma = 8.9$, c: MTV-AW method with $a = 13$, d: The edge map of the MTV-AW method

smoothing result using the proposed method for $a = 5$ pixels is shown in Fig. 3c. The structure of blood vessels has been preserved while reducing random noise throughout the image as illustrated in Fig. 3c.

A. Comparison with state-of-the-art method

To determine the performance with respect to the state-of-the-art methods, our method was compared with the

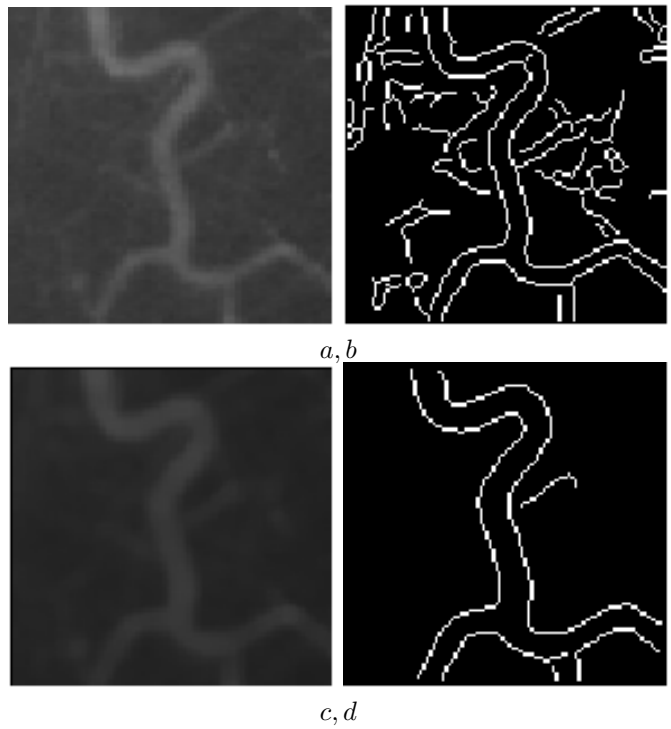

Fig. 3. (a) Original image, (b) The edge map of (a), $\sigma = 10$, (c) Adaptive Total Variation method for $a = 5$ pixels, (d) The edge map of (c) , $\sigma = 10$

MTV method. Recently obtained results in [8] show that this one produce better results than several methods as the total variation minimizing of Rudin et al. [6], the anisotropic diffusion of Perona and Malik [5].

Comparison of the proposed MTV-AW speckle reduction method with the MTV method was applied to ultrasound images of breast cancer and a thyroid, where the proposed method restores and detects image structures better than the MTV method.

Fig. 4(a) and 4(b) show respectively, a breast cancer ultrasound image and canny edge map. Smoothed images using the proposed MTV-AW and the MTV methods are shown in Fig. 4(c) and 4(e), respectively. We notice that the speckle present in the original image is removed by the MTV-AW method and the structure of the tumor has been preserved while this one is less preserved using the MTV method. This is demonstrated on Figs 4(d) and 4(f), which are the edge map of the two results using canny edge detector with the same σ.

Our method is also efficient in terms of accuracy. This is obvious for the thyroid ultrasound image as shown in figure 5, which reveals existence of nodules in the right lobe of the thyroid.

In our tests, different window sizes were used. It has been deduced that a smaller parameter a would retain image noise

while a larger a would smooth noise but also smooth critical image structure. We conclude that the optimal parameter a depends primarily on the image structure and secondarily on the image noise.

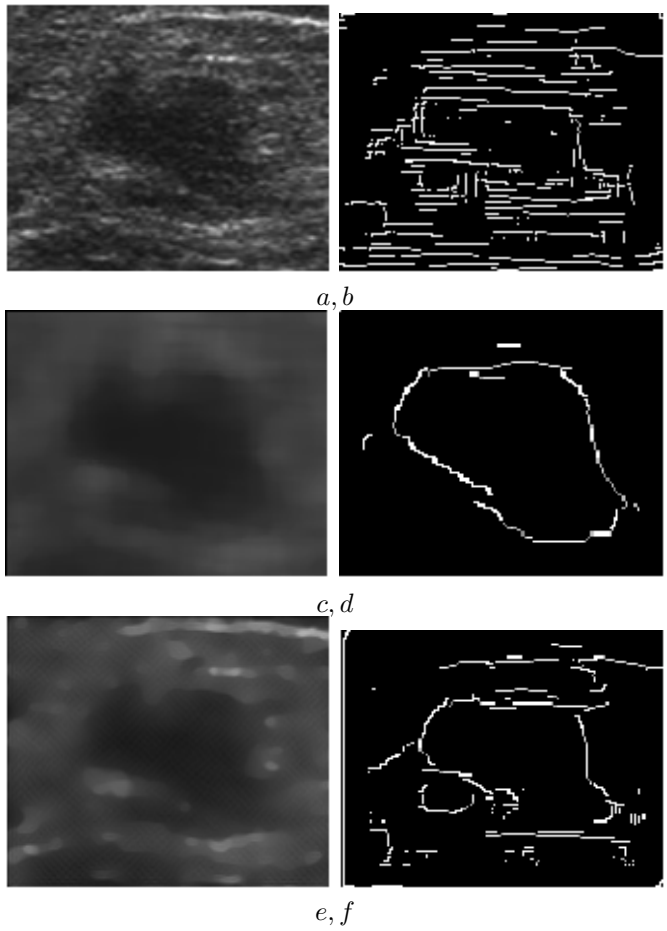

Fig. 4. (a) Original image, (b) The edge map of (a), $\sigma = 13$, (c) MTV-AW method for $a = 9$ pixels, after 1 iteration (d) The edge map of (c) , $\sigma = 10$, (e) Smoothing by the MTV method after $500 iteration$, (f) The edge map of (e), $\sigma = 10$

IV. Conclusion

In this paper, an adaptive total variation method for speckle suppression of medical ultrasound images is proposed. The proposed method adopts an adaptive window with variable size, shape and orientation to calculate the instantaneous Lagrange multiplier. The dynamic window helps to maintain the texture and edge of the image. The adaptive smoothing method is a few times slower than total variation smoothing method. Implementation of the proposed method is very simple. Future work includes improving the filter by taking into account statistical models of the speckle noise.

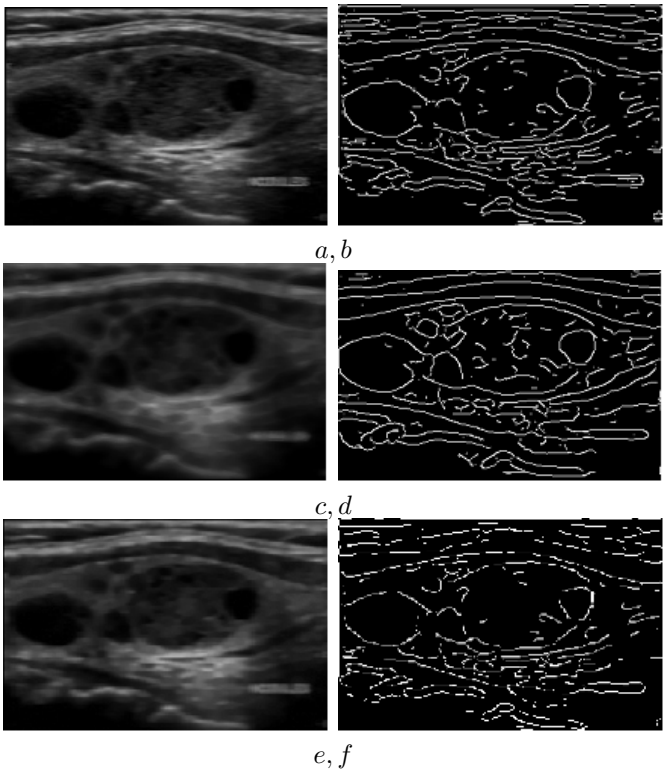

Fig. 5. (a) Original image, (b) The edge map of (a), $\sigma = 3$, (c) MTV-AW method for $a = 9$ pixels, after 1 iteration(d) The edge map of (c) , $\sigma = 3$, (e) Smoothing by the MTV method after $500 iteration$, (f) The edge map of (e), $\sigma = 3$

References

[1] L. C.Zhang, E. M. C. Wong, F. Zhang, and J. Zhou , *Adaptive pyramid filtering for medical ultrasound image enhancement*, 3rd IEEE international Symposium, pp. 916-919, April 2006.

[2] J. S. Lee , *Digital enhancement and noise filtering use of local statistics*, IEEE Transactions on Pattern Analysis and Machine Intelligence 2 (2) 165-168, 1980.

[3] D. T. Kuan, A. A. Sawchuk and T. C. Strand et al, *Adaptive noise smoothing filter for image with signal dependent noise*, IEEE Transactions on Pattern Analysis and Machine Intelligence 7 (2), 165-177,1985.

[4] Y. Yu, S. Acton , *Speckle reduction anisotropic diffusion*, IEEE Transaction on Image Processing (11), pp.1260-1270, 2002.

[5] P. Perona, J. Malik, *Scale-space and edge detection using anisotropic diffusion*, IEEE Transaction. Pattern Anal. Mach. Intell. 12(7) (1990)

[6] S. Osher, L. I. Rudin and E. Fatemi, *Nonlinear total variation noise removal algorithm*, Physica D, no 60, pp. 259-268, 1992.

[7] M. Grasmair, F. Lenzen, *Anisotropic Total Variation Filtering*, Appl Math Optim, no 62,DOI 10. 1007/s00245-010-9105-x, pp. 323-339, 2010.

[8] Khalifa. Djemal, *Speckle reduction in ultrasound images by minimization of total variation*, IEEE Transaction Image Processing, 2005.

[9] P. L. Shui andY. B. Zhao, *Image De noising Algorithm using Doubly Local Wiener Filtering with Block-Adaptive Windows in Wavelet Domain*, Signal Processing 87 , pp. 1721-1734, 2007.

[10] H. Takeda, S. Farsiu, P. Milanfar, *Kernel Regression for Image Processing and Reconstruction*, IEEE Transaction on Image Processing, 16(2), pp. 349-366, 2007.

[11] A. Goshtasby, M. Satter, *An adaptive window mechanism for image smoothing*, Computer Vision and Image Understanding 111, pp. 155-169, 2008.

[12] J. Debayle, J-C. Pinoli, *General Adaptive Neighborhood Choquet Image Filtering*, Journal Math Imaging Vision 35, pp. 173-185, 2009.

[13] W. N. Mc Dicken, T. Loupas and P. L. Allan, *An adaptive Weighted Median filter for Speckle Suppression in Medical Ultrasonic Images*, IEEE Transaction on Circuits and Systems, vol. 36, no. 1, pp. 129-135, 1989.

[14] G. Liu et al, *Speckle Reduction by Adaptive Window Anisotropic Diffusion*, Signal Processing 89 4(4), pp. 2233-2243, 2009.