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SPECKLE REDUCTION IN ECHOCARDIOGRAPHIC IMAGES

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ABSTRACT

Speckle noise is the major difficulty that arises in echocardiographic image processing. Adaptive smoothing techniques for speckle reduction in Two-dimensional echocardiographic images are presented in this paper.

In the first stage, we have applied the Lee, Kuan, and Frost filters, based on the minimum mean square error (MMSE) design approach.

Additionally, anisotropic diffusion method has been used to denoise echocardiographic images. It's a new method derived from convolution with a Gaussian, which allows reducing the noise in the image without blurring the frontiers between different regions.

Criteria for quantifying the performance of the studied filters have been defined and calculated. We cite the ratio of mean grey level, the ratio of speckle index, and the parameter of transition.

Quantitative measurements demonstrate the effectiveness of the anisotropic diffusion filter, for both speckle reduction and edge preservation.

Key-words: speckle reduction, The Lee, Kuan, and Frost filters, anisotropic diffusion, performance criteria, echocardiographic images.

I. INTRODUCTION

For visual analysis of medical images, the clarity of details and the object visibility are important, whereas for image processing a high SNR is required because most of the image segmentation algorithms are very sensitive to noise.

Ultrasound images (USI) are easily acquired, giving both anatomical information (boundaries of anatomical structures usually correspond to variation of the acoustic impedance) and dynamic information (e.g., the heart motion) [1].

Ultrasound US is a commonly used modality for cardiac imaging since it is non-invasive and real time, however echocardiographic images have a high noise content and suffer from poor contrast.

Speckle noise is the major difficulty that arises in echocardiographic image processing. It is generated by reflected waves due to the non-homogenous structure of the tissue, and follow a Rayleigh distributed noise [2], [3]

Speckle degrades the image quality, and hence reduces the ability of a human observer to discriminate the fine details in diagnostic examination. It also decreases the efficiency of further image processing such as edge detection.

Denoising techniques should not only reduce the speckle, but do so without blurring or changing the location of the edges.

In this study, adaptive smoothing techniques for speckle reduction in echocardiographic images are presented. We were interested to a class of adaptive statistical filters based on the same minimum mean square error (MMSE) approach as Lee, Kuan, and Frost filters. In addition, we studied and implemented the anisotropic diffusion filtering to denoise echocardiographic images. This filter not only preserves edges but also enhances edge by inhibiting diffusion across edges and allowing diffusion either side of the edge.

Criteria for quantifying the performance of the studied filters have been defined and calculated. The results are presented in a comparative way.

The paper is organised as follows. In section II we briefly describe the adaptive speckle reduction filters as Lee, Kuan and Frost filters. The nonlinear anisotropic diffusion has reviewed in section III. Section IV defines the criteria for quantifying the performance of the studied filters. In the penultimate section, the results of using filters on real ultrasound images and comparison will be presented, and in the final section we will state our conclusion.

II. ADAPTIVE FILTERS

In this section, we briefly describe the speckle reducing filters: the Lee, Kuan and Frost filters based on the minimum mean square error (MMSE) design approach.

Several techniques of speckle reduction rest on using the multiplicative model according to the following equation:

$$I(i,j)=u(i,j)*b(i,j) \quad (1)$$

Where I(i,j) is the intensity to (i,j) coordinates of the noising image, b(i,j) is the speckle noise and u(i,j) is the denoising image.

The Lee [4], [5], [6] and Kuan [7], [8] filters produce the enhancement data according to:

$$\hat{u}(i,j)=I(i,j)*w(i,j)+\bar{I}(i,j)*(1-w(i,j)) \quad (2)$$

Where $\bar{I}$ is the mean value of the intensity within the filter window, and w(i,j) is the adaptive filter coefficient determined by:

$$w(i,j)=\begin{cases} 1-\dfrac{C_b^{\,2}}{C_I^{\,2}+C_b^{\,2}} & \text{for Lee filter} \\ \dfrac{1-C_b^{\,2}/C_I^{\,2}}{1+C_b^{\,2}} & \text{for Kuan filter} \end{cases} \quad (3)$$

Where $C_I=\dfrac{\sigma_I}{\bar{I}}$ is the coefficient of variation of the noising image and $C_b=\dfrac{\sigma_b}{\bar{b}}$ is the coefficient of variation of the noise [9].

Generally, the value of w(i,j) approaches zero in uniform areas, leading to the same result as that of the mean filter. In the other hand, the value of w(i,j) approaches unity at edges, resulting in little modification to the pixel values near edges.

The Frost filter [10] uses an exponentially damping convolution kernel that adapts to regions containing edges by exploiting local statistics. The filter output is determined by:

$$h(i,j)=K_2*e^{-K_1*C_I^{\,2}*I(i,j)} \quad (4)$$

Where K_2 is a constant of standardization and K_1 is the damping factor.

The factor K_1 is chosen such that when in a homogeneous region $K_1C_1^2$ approaches zero, yielding the mean filter output, at an edge $K_1C_1^2$ becomes so large that filtering is inhibited completely.

III. ANISOTROPIC DIFFUSION

III.1 Formalism

It's a new method derived from the convolution with a Gaussian, which allows reducing the noise in the image without blurring the frontiers between different regions.

Mathematically, the anisotropic diffusion process is defined as follows [11], [12]:

$$\frac{\partial I(x,y,t)}{\partial t}=div\,(g(|\nabla(I(x,y,t)|).\nabla(I(x,y,t)) \quad (5)$$

$$I(x,y,0)=I_0(x,y) \quad (6)$$

Where ∇ is the gradient operator, *div* divergence operator, | | denotes the magnitude, and I_0 is the initial image.

I(x,y,t) represents the intensity function of the echocardiographic image. The variable t is the processing ordering parameter in the discrete implementation. It is used to enumerate iteration steps. The diffusion function $g(|\nabla(I(x,y,t)|)$ depends on the magnitude of the gradient of the image intensity. It is a monotonically decreasing function which mainly diffuses within regions and does not affect region boundaries at locations of high gradients.

Deriche and Faugeras [13] proposed a variationnal approach of this problem. It consists in interpreting equation (1) as a descent of the gradient to minimize the following energy E (I):

$$E(I)=\int_{\Omega}\varphi\,(|\nabla(I)|)\,d\Omega \quad (7)$$

Where $$g(|\nabla I|)=\frac{\varphi'\ (|\nabla I|)}{|\nabla I|} \quad (8)$$

The minimum of the energy E (I) verify the Euler-Lagrange equation: $\nabla E=0$

Equation (1) becomes:

$$\frac{\partial I}{\partial t}=-\nabla E=\varphi''(|\nabla I|)\,u_{\xi\xi}+\frac{\varphi'(|\nabla I|)}{|\nabla I|}\,u_{\eta\eta} \quad (9)$$

Where $\xi=\dfrac{\nabla I}{|\nabla I|}$ a unit is vector in the direction of the gradient, and η is a normal vector orthogonal to the gradient.

The convergence of this process is ensured for diffusion functions g with given properties [13]. Krissan and al [14] referenced only three functions that satisfy all of the criteria. The function chosen for testing this diffusion is the function proposed by Aubert [9] defined by the following equation:

$$\phi(|\nabla I|\ ) = \sqrt{1+\left(\frac{\nabla I}{k}\right)^2} \quad -1 \tag{10}$$

This function satisfies the properties of stability and restoration for the Perona and Malik process [10].

The conductance parameter K enables backward diffusion when it is smaller than the gradient I, thus enhancing the edges.

III.2 Discrete implementation

The discrete implementation of the non linear anisotropic diffusion filter rest on three key ideas:

1- In the discrete domain, a gradient or derivative can be approximated as the difference in intensity between neighboring elements in the image.
2- The function $\phi(I)$ can be calculated independently for each neighboring elements.
3- The filter is iterative; the right hand of equation (1) describes the change in image intensity produced by one iteration of the filter.

Using these ideas, a 2D derivation for the filter will be described [14], [15].

$$\begin{aligned}
\frac{\partial I(x,y,t)}{\partial t} &= div(g(|\nabla(I(x,y,t)|).\nabla(I(x,y,t)) \\
&= \frac{\delta}{\delta x}\left[g(x,y,t).\frac{\delta}{\delta x}I(x,y,t)\right] + \frac{\delta}{\delta y}\left[g(x,y,t).\frac{\delta}{\delta y}I(x,y,t)\right] \\
&\approx \frac{1}{(\Delta x)^2}\begin{bmatrix} g(x+\frac{\Delta x}{2},y,t).(I(x+\Delta x,y,t)-I(x,y,t)) \\ -\,g(x-\frac{\Delta x}{2},y,t).(I(x,y,t)-I(x-\Delta x,y,t)) \end{bmatrix} + \\
&\quad \frac{1}{(\Delta y)^2}\begin{bmatrix} g(x,y+\frac{\Delta y}{2},t).(I(x,y+\Delta y,t)-I(x,y,t)) \\ -\,g(x,y-\frac{\Delta y}{2},t).(I(x,y,t)-(I(x,y-\Delta y,t)) \end{bmatrix} \\
&= \varphi_{east} - \varphi_{west} + \varphi_{north} - \varphi_{south}
\end{aligned} \tag{11}$$

The filtering process consists of updating each pixel in the image by an amount equal to the flow contributed by its four nears neighbours:

$$I(x,y,t+\Delta t) \approx I(x,y,t) + \Delta t\,.(\varphi_{east} - \varphi_{west} + \varphi_{north} - \varphi_{south} \tag{12}$$

IV. EVALUATION CRITERIA

Additionally to subjective visual evaluation, it is desirable to present quantitative results of speckle reduction. In our experiments, we are quantifying the performance of using filters in terms of edge preservation, mean preservation in a homogenous region and variance reduction in a homogenous region. For that**,** we have been defined three statistical criteria of performance: The ratio of means grey level RM, the ratio of speckle index RSI, and the parameter of transition PT. In addition, we have compared the histograms of the images before and after filtering.

IV.1 Ratio of Means grey level RM

This criterion is used for showing the filter capacity to preserve the homogeneous region contrast after filtering. It is given by:

$$RM = \frac{\mu_2}{\mu_1} \tag{13}$$

Where μ_1 et μ_2 are respectively the intensity mean over a homogeneous region of the image before and after filtering.

IV.2 Ratio of Speckle Index RSI

This criterion indicates the filter capacity to reduce the noise in homogeneous region. It is given by [16]:

$$RSI = \frac{C_1 - C_2}{C_1} \tag{14}$$

Where C_1 and C_2 are respectively coefficients of variation before and after filtering.

IV.3 Parameter of Transition PT

To compare edge preservation performances of different speckle reduction schemes, we adopt the parameter of transition, defined by:

$$PT = \frac{\mu_2 - \mu_1}{\mu_2 + \mu_1} \tag{15}$$

Where μ_1 et μ_2 are respectively the means of two homogenous regions of the same gray level.

This parameter indicates the capacity of the filter to restore the transition, the higher this number, the better the effect of the denoising in term of edge localisation.

VI. EXPERIMENTAL RESULTS

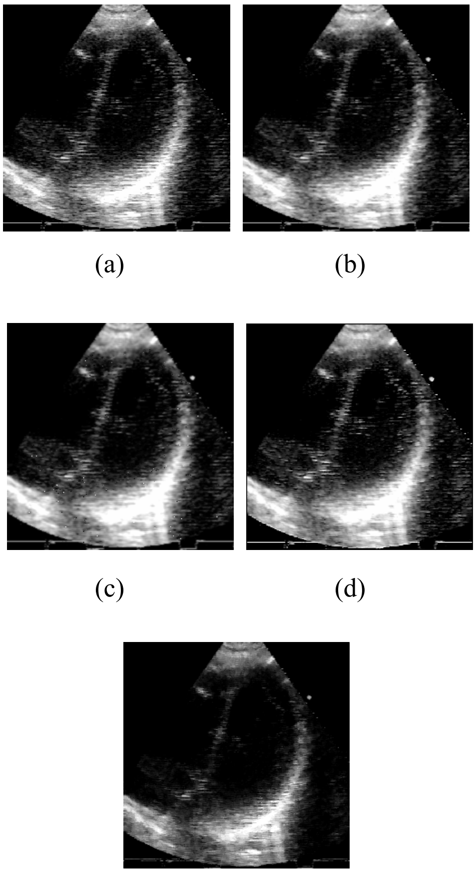
In this section, we describe the results of our experiments using adaptive smoothing techniques to denoise echocardiographic images with have been corrupted by multiplicative noise.

The filtered schemes have been applied to 2D image data representing the left ventricle of patient heart. For echographic data, we used a 5-MHz mechanical probe to a Ving Med CFM750 echographic system [17].

The adaptive speckle reduction filters namely the Lee, Kuan and Frost filters were tested using a region size of 5*5 pixels, and a noise coefficient of variation C_b=0.40.

The anisotropic diffusion filter was tested with various numbers of iteration. The parameter K is typically done experimentally

The filtering results are represented in figure 1.

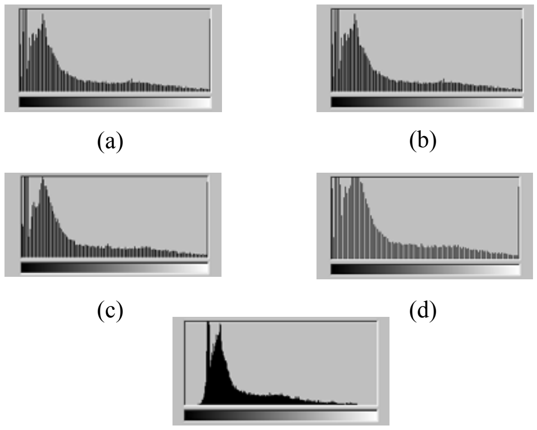


(a) (b) (c) (d) (e)

FIG 1: a) original noisy image, (b)-(e) :Filtered echocardiographic images using Lee, Kuan, Frost and anisotropic diffusion filters

A visual analysis of these images clearly shows that the anisotropic diffusion algorithm provides superior performance in comparison to the adaptive filters namely Lee, Kuan, and Frost, in terms of smoothing uniform regions and preserving edges.

Additionally, we have analyzed the histograms of images data, original and filtered, (see fig 2) where axis X corresponds to intensity (from 0 to 255) and axis Y represents the numbers of pixels to each grey level.



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

FIG 2 : Intensities histograms : (a) original noisy image , (b)-(e) : Filtered echocardiographic images using Lee, Kuan, Frost and anisotropic diffusion filters

Figure 2 depicts the anisotropic diffusion effect on the intensities histogram. The anisotropic diffusion filter clearly reduces the principal peak width (comparatively to Lee, Kuan, and Frost filter) i.e. reduces the dispersion of the intensities, and thus more clearly releases this peak of the other values.

In addition to subjective visual evaluation, the quantitative results of speckle reduction are presented in Table I.

Table I : Performance criteria of studied filters

	RM (%)	**RSI (%)**	**PT(%)**
Lee filter	67.02	12.81	15.50
Kuan filter	68.08	33.26	13.45
Frost filter	74.67	34.16	25.69
Anisotropic diffusion	97.87	94.35	45.87
Ideal value	100	100	50

Table I summarizes the performance criteria of the four filtering techniques. The ration of means, the ration of speckle index, and the parameter of transition are computed for each filtering schema. The test areas are chosen in homogeneous regions using PC mouse. The test area size is 5*5 pixels.

These quantitative results shown the advantages of anisotropic diffusion filter include intra-region smoothing and edge preservation. The anisotropic diffusion filtered image appears clearer and boundaries are much better defined. This filter illustrates the efficient noise reduction in homogeneous regions. Left ventricle contour is not only preserved, but even enhanced.

CONCLUSION

We conclude that the anisotropic diffusion filter combines a highly efficient noise reduction and the ability to preserve and even enhance edges of the left ventricle, comparatively to Lee, Kuan, and Frost filters. The anisotropic diffusion filter is shown to produce images that are better inputs for subsequent feature extraction. However, improvements are possible:

- Using a rotating probe combined with an ECG gating technique we acquire trans-thoracic images database. Thus, these images are acquired in spherical coordinates. Several methods are possible to calculi gradient, but these methods are not equivalent.
- The threshold K is a significant parameter in diffusion process. In the anisotropic diffusion method, the gradient magnitude is used to detect an image edge or boundary as a step discontinuity in intensity. If $|\nabla I| >> k$, then $g(|\nabla(I)|) \rightarrow 0$, and we have an all-pass filter so that the diffusion is "stopped" across edges; if $|\nabla I| << k$, then $g(|\nabla(I)|) \rightarrow 1$ and we achieve isotropic diffusion (Gaussian filtering). K can be to fix using the intensities histogram or the statistical properties of the homogeneous areas.

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