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Biomedical Ultrasound Image Enhancement using SRAD

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ABSTRACT

In this paper we present Speckle Reducing Anisotropic Diffusion (SRAD) technique that uses wavelet decomposition. This technique is able to preserve and enhance edges while smoothing homogeneous regions in ultrasound images. SRAD is applied on various real biomedical ultrasound images with different number of iterations. The performance of SRAD filter is found to be much better than conventional Lee, Frost filters. SRAD gives less MSE, higher PSNR and better FOM. The experiemental results show that this technique works effectively both in terms of speckle reduction, edge preservation and edge enhancement.

General Terms

Techniques, Experiements.

Keywords

Image Enhancement, SRAD

1. INTRODUCTION

Ultrasound imaging, also called biomedical scanning or sonography, involves exposing part of the body to high-frequency sound waves to produce picture of the internal organs.

It is non-invasive, non-ionizing, portable, low cost and real time image formation medical test. However, in medical ultrasound imaging, the quality of the image is generally corrupted by a form of locally correlated multiplicative noise called speckle. Speckle occurs in all type of coherent imagery such as Synthetic Aperture Radar (SAR) imagery, acoustic imagery, and laser illuminated imagery. Speckle reduction usually represents a critical preprocessing steps for high quality ultrasound images, providing physicians with enhanced diagnostic ability. Without speckles, it is more possible to observe the small high contrast targets, low contrast objects, as well as tissue boundaries.

Anisotropic diffusion has been widely used to reduce speckle noise from ultrasound images. Diagnosis of ultrasound images are very difficult because the existence of speckle which hamper the prediction and the extraction of fine details from the image. So the quality of the image can be improved by using speckle reduction (techniques) filtering. Earlier filters aim to reduce speckle, such as Lee and Frost are based on the coefficient of variation. Then, based on previous research, Yu and Acton have proposed a Speckle Reducing Anisotropic Diffusion(SRAD)filter. SRAD is able to smooth homogeneous regions of speckle while preserving and enhancing feature edges. The SRAD is directly related to Lee and Frost window-based filters. So, SRAD is the edge sensitive extension of conventional adaptive speckle filter, in the same manner that the original Perona and Malik anisotropic diffusion is the edge-sensitive extension of the average filter [4].

2. METHODOLOGY

2.1 Wavelet Decomposition

It has important application in signal processing problems such as image coding and image de-noising. The principle of wavelet decomposition is to transform the original raw particle image into several components: one low resolution, and one high resolution .The noise is mainly appeared in the details. By repeating this process, it is possible to obtain wavelet transform of any order [8].

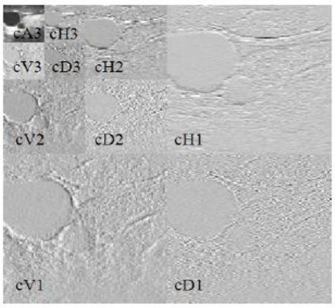


Figure.1.1 The results of multi scale wavelet decomposition for clinical ultrasound image.

2.2 Design considerations:

Speckle Filtering

Speckle filtering consists of moving a kernel over each pixel in the image and applying a mathematical calculation using the pixel values under the kernel and replacing the central pixel with the calculated value. The kernel is moved along the image one pixel at a time until the entire image has been covered. By applying the filter a smoothing effect is achieved and the visual appearance of the speckle is reduced.

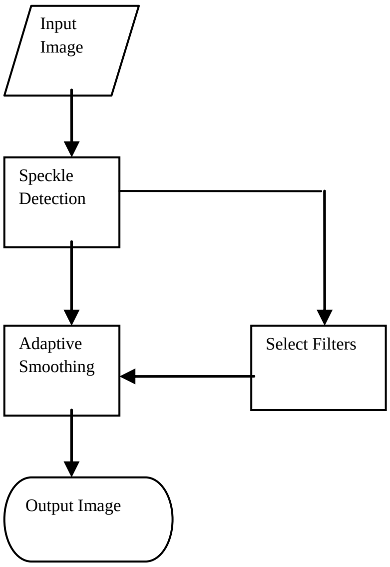


Figure. 2.1 Functional blocks of ultrasound image enhancement

3. EXPERIEMENTS

3.1 Lee Filter

The Lee filer is designed to eliminate speckle noise while preserving edges and point features in radar imagery. Based on linear speckle noise model and the minimum mean square error (MMSE) design approach, the filter produces the enhanced data according to

$$\hat{I}s = \bar{I}s + k_s(Is - \bar{I}_s)$$

where $\bar{I}s$ is the mean value of the intensity, within the filter window ηs ; and k_s is the adaptive filter coefficient determined by

$$k_s = 1 - C_u^2/C_s^2$$

Here, $Cs^2 = (1/|\eta_s|) \sum_{p\in\eta} (Ip - \bar{I}s)^2 /(Ip - \bar{I}s)^2$

and C_u^2 is a constant for a given image and can be determined by either

$$C_u^2 = 1 / ENL$$

Or

$$C_u^2 = \frac{\text{var}(z')}{(\bar{z}')^2}$$

where ENL is the effective number of looks of the noisy image. This parameter is used to derive noise variance. By adjusting ENL, the user can control the amount of smoothing applied to the image. Theoretically, the correct value of ENL should be the effective number of looks of the radar image. It should be close to the actual number of looks, but may be different if the image has undergone resampling. A smaller value leads to more smoothing; a larger value preserves more image features. The ENL factor is related to the radiometric resolution of the image.

var(z') and $(\bar{z}')^2$ are the intensity variance and mean over a homogeneous area of the image, respectively. The local statistic Cs plays an essential role in controlling the filter: if Cs → Cu, then k_s → 0, and ,if Cs → ∞ , then k_s → 1 . In general the value of k_s approaches zero in uniform areas, leading to the same result as that of the mean filter. On the other hand, the value of k_s approaches unity at edges, resulting in little modification to the pixel values near edges.The use of large values for damping factor allows for better preservation of sharp edges, but reduces the smoothing effect. The use of small values for damping factor increases the smoothing effect, but does not preserve sharp edges well. Lee performs spatial filtering on each individual pixel in an image using the grey level values in a square window surrounding each pixel. The dimensions of the filter must be odd, and must be at least 3 * 3.

3.2 Frost Filter:

The Frost filter strikes balance between averaging and all-pass filter. In this case, the balance is achieved by forming an exponentially shaped filter kernel that can vary from a basic average filter to an identity filter on a point wise adaptive basis. Again, the response of the filter varies locally with the coefficient of variation . In case of low coefficient of variation, the filter is more average like, and in case of high coefficient of variation, the filter attempts to preserve sharp features by not averaging[4].

The Frost filter uses an exponentially damped convolution kernel that adapts to regions containing edges by exploiting local statistics. The filter output is determined by

$$\hat{I}_s = \sum_{p\in\eta s} m_p I_p$$

where

$$m_p = \exp(-KC_s^2 d_{s,p}) \Big/ \sum_{p\in\eta} \exp(-KC_s^2 d_{s,p})$$

and

$$ds,p = \sqrt{(i - i_p)^2 + (j - j_p)^2}$$

Where K is the damping factor, (i,j) are the grid coordinates of pixel s, and (i_p, j_p) are those of pixel p.

The factor K is chosen such that when in a homogeneous region KC^2s approaches zero, yielding the mean filter output; at an edge KC^2s becomes so large that filtering is inhibited completely [4].

3.3 SRAD Filter :

The SRAD filter has been described using combining the anisotropic diffusion and Lee filter. SRAD is derived by the instantaneous coefficient of variation (ICOV) in the same way as Lee filter into a partial differential equation (PDE) framework. Given an image having finite power and non-zero valued intensities over the image domain, the continuous form of SRAD's PDE is expressed as follows –

$$\begin{cases} \dfrac{\partial I(u,v;t)}{\partial t} = div[c(q)\nabla I(u,v,;t)] \end{cases}$$

$$I(u,v;0) = I_0(u,v), \left(\frac{\partial I(u,v,;t)}{\partial \overline{\eta}}\right) |_{\partial\Omega} = 0$$

where ∇ the gradient operator; div the divergence operator; I(u,v;t) the intensity image estimated at position u, v, at time t; $\partial\Omega$ denotes the border of the image support Ω , while $\overline{\eta}$ is the outer normal to $\partial\Omega$; $c(q)$ is the diffusivity function of SRAD defined as –

$$c(q) = \frac{1}{1 + \dfrac{[q^2(u,v;t) - q_0{}^2(t)]}{[q_0{}^2(t)(1+q_o{}^2(t))]}}$$

where $q(u,v;t)$ defined as –

$$q = \sqrt{\frac{(1/2)(|\nabla I|/I^2 - (1/4^2)(\nabla^2 I)/I)^2}{[1+(1/4)(\nabla^2 I/I)]^2}}$$

and q, can be described as –

$$q_0(t) = \frac{\sqrt{\mathrm{var}[z(t)]}}{z(\bar{t})}$$

where q(u,v;t) is ICOV, and q_0 is diffusion threshold called speckle scale function that computed from a homogeneous region of fully developed speckle. The var[z(t)] and z(t) are intensity variance and mean over a homogeneous area at time t. ICOV is a function of the image normalized gradient magnitude ∇ I / I and the normalized Laplacian ∇^2I /I defined in relation with the adaptive coefficient of the Lee filter. Also, q_0 and c_u^2 are diffusion thresholds that have same casting. Furthermore, q(u,v;t) and q_0 act as edge detector η in nonlinear diffusion and the diffusion threshold λ .

Analytical form of scale function $q_o(t)$:

Because of the need of computing (39), the SRAD requires knowing a homogeneous area inside the image being processed. Although it is not difficult for a user to select a homogeneous area in the image, Although it is not difficult for a user to select a homogeneous area in the image, it is nontrivial for a computer .So, automatic determination of $q_o(t)$ is desired in real application to eliminate heuristic parameter choice.

First of all, we state that $q_o(t)$ can be approximated by

$$q_o(t) = q_o \exp[-\rho t]$$

where ρ is a constant, and q_o is the speckle coefficient of variation in the observed image. For fully developed speckle, $q_o = 1$ for ultrasound intensity data (without compounding and $q_o = 1/\sqrt{N}$ for N-look SAR intensity data .For partial correlated speckle, q_o is less than unity.

Now, we give the derivation of (32). As we expected, in a uniform area the diffusion should be isotropic. Adopting the discrete isotropic diffusion update, we have

$$I_{i,j}^{t+1} = I^t i,j + \frac{\Delta t}{4} (I^t_{i+1,j} + I^t_{i-1,j} + I^t_{i,j+1} + I^t_{i,j-1} - 4I^t_{i,j}).$$

4. EVALUATION PARAMETERS

In order to evaluate the results of filter quantitatively, the following four parameters are defined and evaluated-

$$MSE = (1/k) \sum_{i=1}^{k} (\hat{S}i - Si)^2$$

where, Si , $\hat{S}i$ represent the original and denoised images, respectively. k represents the image size.

MSE actually measures the closeness of the image after speckle reduction to the original real speckle free image. Since for ultrasound images there is actually no "original" speckle free image for comparison, this measure can not be applied for assessing quality of ultrasound images. Instead, it can only be used to quantify the quality of simulated images, where the original image is available. The smaller the MSE value is, the better the speckle reduction filter performs.

$$PSNR = 10 * \log_{10} \left(255^2 / \mathrm{MSE} \right)$$

$$S/MSE = 10 * \log_{10} \left(\sum_{i=1}^{k} Si^2 / \sum_{i=1}^{k} \left(\hat{S}i - Si\right)^2 \right)$$

$$FOM = \frac{1}{\max\{\hat{N}, N_{ideal}\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + di^2 \alpha}$$

where $\hat{N}$ and N_{ideal} are the number of detected and ideal edge pixels, respectively, d_i is the Euclidean distance between the ith detected edge pixel and the nearest edge pixel, and α is a constant typically set to 1/9. FOM ranges between 0 and 1, with unity for ideal edge detection.

Mean M = sum of x values / N

where N is number of values.

$$\text{Standard Deviation } s = \sqrt{\frac{\sum (x - M)^2}{n - 1}}$$

where M is mean.

5. RESULTS

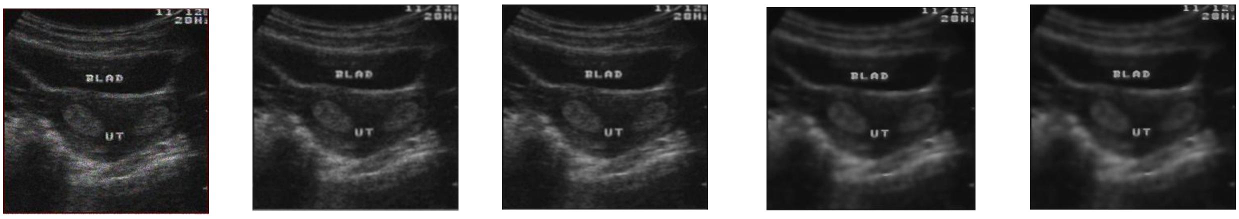
The performance of the Frost filter, Lee filter and SRAD filter is investigated with simulations on real ultrasound images. Denoising is carried out for ultrasound image with speckle noise. For objective evaluation, the peak signal to noise ratio (PSNR),Mean square error (MSE), Signal to Noise ratio (S/MSE), and Pratt's figure of Merit (FOM), Mean and Standard Deviation of each denoised image has been calculated.

All the simulations have been done in MATLAB tool.

Table 1. Comparison of PSNR, MSE, S/MSE, FOM, Mean and Standard Deviation of real ultrasound images without addition of speckle noise .

Image	Filter	PSNR	MSE	S/MSE	FOM	Mean	Std. Dev.
1	Lee	25.272	193.10	10.802	0.301	41.81	8.012
	Frost	33.602	28.367	18.365	0.469	42.65	7.874
	SRAD(15 iter)	79.649	0.007	16.963	0.539	0.153	0.108
	SRAD(20 iter)	78.809	0.008	16.058	0.558	0.153	0.107
2	Lee	24.162	224.158	15.278	0.197	81.379	9.87
	Frost	28.61	89.55	18.851	0.338	82.513	9.876
	SRAD(15 iter)	74.776	0.002	17.428	0.446	0.323	0.162
	SRAD(20 iter)	73.98	0.002	16.578	0.465	0.323	0.16
3	Lee	26.316	151.869	9.165	0.314	48.689	8.39
	Frost	32.645	35.363	17.258	0.327	49.68	8.381
	SRAD(15 iter)	76.676	0.001	15.072	0.338	0.165	0.135
	SRAD(20 iter)	76.321	0.001	14.54	0.342	0.165	0.134
4	Lee	24.541	228.547	1.455	0.127	62.487	9.227
	Frost	27.746	109.246	11.668	0.171	63.543	9.086
	SRAD(15 iter)	72.735	0.003	7.412	0.206	0.249	0.135
	SRAD(20 iter)	72.014	0.04	6.299	0.199	0.25	0.134

5	Lee	21.577	452.172	1.89	0.224	111.312	9.418
	Frost	24.71	219.791	17.056	0.255	113.052	9.408
	SRAD(15 iter)	71	0.004	15.381	0.331	0.437	0.167
	SRAD(20 iter)	71	0.005	13.79	0.341	0.438	0.164



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

Fig 2: The visualization results of real ultrasound images: (a) Original image (b) Lee filtered image (c) Frost filtered image (d) SRAD with 15 iterations image (e) SRAD with 20 iterations image

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7. REFERENCES
[1] B.Yoo and T. Nishimura , "A Study of Ultrasound Image Enhancement Using Adaptive Speckle Reducing Anisotropic Diffusion," presented at IEEE International Symposium on Industrial Electronics ,pp.: 581-585,2009.

[2] K. Krissian, R. Kikinis and K.G.Vosaburgh,"Oriented Speckle Reducing Speckle Diffusion," presented at IEEE ransactions on Image Processing,vol.16, No.5,May 2007.

[3] Y.Yu and J.Yadegar , "Regularized Speckle Reducing Anisotropic Diffusion for Feature Characterization," presented at IEEE International Conference 2005.

[4] Y. Yu and S.T. Acton, "Speckle reducing anisotropic diffusion, "IEEE Trans. Image Process., vol. 11, no.11,pp. 1260-1270,Nov. 2002.

[5] S. T.Acton, "Deconvolutional Speckle Reducing Anisotropic Diffusion," presented at Image Processing, 2005, ICIP 2005. IEEE International Conference on, 2005.

[6] S. Sudha, G. R. Suresh and R. Sukanesh, "Speckle Noise Reduction in Ultrasound Images by Wavelet Thresholding based on Weighted Variance," International Journal of Computer Theory and Engineering, Vol.1, No.1, April 2009.

[7] X. Zhi, T. Wang, "An Anisotropic Diffusion Filter for Ultrasonic Speckle Reduction," presented at Institution of Engineering and Technology 2008.

[8] B. Yoo, H. Park, J. Ryu, K. Hwang, T. Nishimura, "Wavelet Decomposition Based Speckle Reduction Method for Ultrasound Images by Using Speckle Reducing Anisotropic Diffusion," presented at World Congress on Engineering and Computer Science,2008.

[9] M. Mansourpour, M.A.Rajabi, J.A.R. Blais, "Effects and performance of speckle noise reduction filters on active radar and SAR images" .

[10] Li Ri, S. Zhuoxin, Z. Cishen, "Adaptive Filter for Speckle Reduction with Feature Preservation in Medical Ultrasound Images," presented at 10th Intl. Conf on Control, Automation, Robotics and Vision, December 2008.

[11] S. K. Narayanan, R.S. D. Wahidabanu, "A view of Despeckling in Ultrasound Imaging," International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 2, no.3, September 2009.