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A Novel Approach for Minimization of Speckle Noise in Ultrasound Imaging Using Redundant Discrete Wavelet Transform

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ABSTRACT *: In medical, ultrasound imaging techniques are used for diagnosis purposes. Ultrasound image comprises of speckle noise, which often leads to the confusion for making the clinical decisions during diagnosis. In over viewing the difficulty that had encountered, we had come up with a technique which minimizes the speckle noise in ultrasound image to a greater extent. A technique was adapted to accomplish the issues arrived during the imaging was redundant discrete wavelet transform (RDWT), which comprises estimation of generalized gamma distribution method and Bayesian shrinkage function for minimization of noise in ultrasound images. With the use of this algorithm for the proposed technique we can obtain quantitative parameters that are capable of producing the key ultrasound images which in turn makes the things very feasible in analyzing and diagnosing the vital parameters for the clinical examination purpose.*
Keywords*: Ultrasound image, speckle noise, RDWT, Bayesian shrinkage function estimator.*

I. INTRODUCTION

Ultrasonography is considered to be one of the most powerful technique for imaging organs and soft tissue structures in human body.
The main objective of image denoising technique is to remove speckle noises while retaining as much as possible the important image features. The use of ultrasound (US) in diagnosis is well established because of its non-invasive nature, low cost, capability of forming real time imaging and continuing improvement in image quality [1]. The basic properties of speckle are described by Goodman [2, 4]. The statistical description of the speckle noise generally depends upon the tissue composition and type.

Current speckle reduction methods are based on temporal averaging, median filtering, and Wiener filtering. The adaptive weighted median filter can effectively suppress speckle but it fails to preserve many useful details. The classical Wiener filter, which utilizes the second-order statistics of the Fourier decomposition, is not adequate for removing speckle since it is designed mainly for additive noise suppression. To address the multiplicative nature of speckle noise, Jain developed [5] a homomorphic approach, which by taking the logarithm of the image, Converts the multiplicative into additive noise, and consequently applies the Wiener filter.

II. SPECKLE NOISE IN ULTRASOUND IMAGES

2.1 Speckle image model:

It is well established that the fully‐developed speckle is a multiplicative noise [5] and can be modeled as

$I_s=\eta Z_{de}$ ……………………………………………………. (1)

Where I_s, η, Z_{de} Original image consisting noise, noise component, denoise image respectively.

Generally the effect of additive component of speckle in ultrasound image is less significant than the multiplicative component. When logarithmic transformation applied to both sides of (1), converts the multiplicative noise into an additive one.

$\log I_s = \log(\eta . Z_{de})$

$I_{s1}=\eta_1+Z_{de1}$ ……………………………………….... (2)

2.2 Discrete Wavelet Transform (DWT):

The DWT of an image is implemented by filtering with a pair of quadrature mirror filters along the rows and columns alternatively, followed by downsampling by a factor of two in each direction [10]. This filtering operation decomposes the image into four sub-bands LL, HL, LH, and HH. The LL sub-band contains the low frequency components in both directions, where HL, LH, and HH sub-bands contain the detail components in horizontal, vertical, and diagonal directions, respectively [10]. The above filtering process is iterated on the LL sub-band, splitting it into four smaller sub-bands in the same way. The entire process is computed using a tree-structured filterbank.

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2.3 Redundant Discrete Wavelet Transform (RDWT):

The decimators remove redundant coefficients, which are not necessary to perfectly reconstruct the signal. This makes wavelet compression algorithms more computationally efficient. In wavelet techniques the redundant coefficients are useful. Decimation removes potentially valuable information. In cases like this it is beneficial to remove the decimators. The redundant discrete wavelet transform (RDWT) [6, 7] is a special version of the DWT that preserves instead of downsampling, the RDWT utilizes recursively dilated filters in order to halve the bandwidth from one level to another.

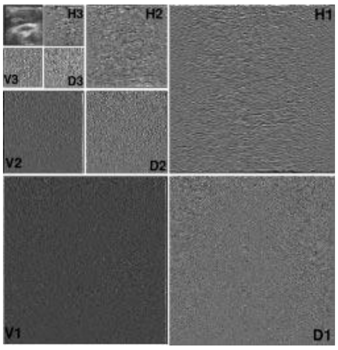

Fig. 1: Three-scale decomposition of an ultrasound image.

$W(I_1)=W(\eta_1+Zde_1)=W(\eta_1)+W(Zde_1)$ …………………………….……(3)

The wavelet transform now becomes a linear operation thus; the application of the RDWT to the noisy image, I_1 gives [1]
Where, W is the RDWT operator for notational simplicity, Equation (3) is rewritten as

$Y=N+X$…………………………………………………………….... (4)

Where Y, X, and *N* are the random variables representing wavelet coefficients of the noisy data, noise‐free data, and the noise, respectively in Equation (2).

III. STATISTICAL MODELING OF RDWT COEFFICIENTS

3.1 Probability density function of random variable X:

Probability density function of random variable X is define as [10]

$f(x) = \frac{dF(x)}{dx}$ ………………………………………..………………….. (5)

For the PDF of discrete random variable X taking on values $x_1,x_2,.. x_n$ with point masses p_i is defined by

$f(x)=\frac{dF(x)}{dx}=\sum_{i=1}^{n} p_i(\delta(xx_i))$…………………………………………………... (6)

The PDF of a generalized gamma‐distributed Random variable X that is gamma distributed with shape K and scale ϴ

$X\sim F(k, \Theta) = \text{Gamma}(k, \Theta)$………………………………………………….. (7)

PDF using shape and scale parameter [1] the probability density function using the shape-scale parameterization is

$f(x,k,\Theta)=\frac{x^{k-1}e^{\frac{-x}{\Theta}}}{\Theta^k\,\gamma(k)}$ for $x>0$, $k, \Theta>0$ ……………………………………..……..(8)

Where, ϴ is scale parameter, k is shape parameter.

3.2 The PDF of a generalized gamma Wavelet
Coefficients (N):

We have used the two‐sided GGAD model for approximating the speckle wavelet coefficients (N) [14, 1]. The probability density function using the shape-scale parameterization is

f (n, k, Θ) = $\frac{n^{k-1} e^{\frac{-n}{\Theta}}}{\Theta^{k}\, \gamma(k)}$ for n>0, k, Θ>0..(9)

4: Speckle reduction through Bayesian speckle suppressor:

4.1 Derivation of the Bayesian shrinkage functions:

P (B|A) = $\frac{P(A|B).P(B)}{P(A)}$ …………………………………………………….... (10)

P (A): Probability of occurrence of event A

P (B): Probability of occurrence of event B

P (*B*|*A*): Probability of occurrence of B given that A has occurred (conditional)

Using Bayes rule, a posterior PDF of X based on the observed data Y, can be expressed as

P (X|Y) = $\frac{P(Y|X).P(X)}{P(Y)}$ ……………………………………………….….……. (11)

P (X|Y): Probability of occurrence of X is given that Y has occurred

In the Bayesian framework, the MAP estimate of the signal, X, is obtained by maximizing a posterior density function [3] Our goal is to find the Bayes risk estimator $x^{\wedge}$ that minimizes the conditional risk, which is the loss averaged over the conditional distribution of x

$X^{\wedge}$ = arg min $x^{\wedge} \int L$[x, $x^{\wedge}$ $P_{x^{\wedge}}(x^{\wedge})$] d……………….…………………………..… (12)

Therefore, the MAP estimate $X^{\wedge}$ is given by the condition [11, 16]

$x^{\wedge} = \int x P_{x^{\wedge}}(x^{\wedge})$ dx ……………………………………………………………… (13)

IV. SELECTION OF PARAMETERS:

By assuming Gaussian PDF and Laplacian density for the signal wavelet coefficients we see [1] that $x^{\wedge}$ is a function of Y, σ_X, K, and Θ. In absence of the true values, we have to estimate them as follows.

5.1 Estimation of σ^2_X :

To adapt the estimator to the local image statistics, the value of the parameter, σ^2_X , is to be computed for each wavelet coefficients from the local neighbourhood [1, 19] Since X and N are zero mean and independent, we get

$\sigma^2_y = \sigma^2_X +$ …………………………………………………….………………(14)

The estimation of spatially varying parameter, $\hat{\sigma}_x$, at a given spatial position can be computed as

$\hat{\sigma}_x = \sqrt{\max(\sigma_y^{\wedge 2} - \sigma_N^2, 0)}$…………………………………………..…. (15)

Here, $\sigma^{\wedge 2}_y$ and, σ_N^2 are the estimated variance of the noisy wavelet coefficients, *Y* and the noise, *N*, respectively ,$\sigma^{\wedge 2}_y$ can be obtained by

$\hat{\sigma}_y = \sqrt{\frac{1}{t^2} \sum_{l,k \varepsilon N_i} Y_{l,k}^2}$ ……………………………………………………….….. (16)

Where, N_i is the window size of t x t cantered at *i* and Y_l, *k* is the wavelet coefficient in the detailed subband at location (1, *k*). $\sigma^{\wedge 2}_y$ in Equation (15) is estimated as follows.

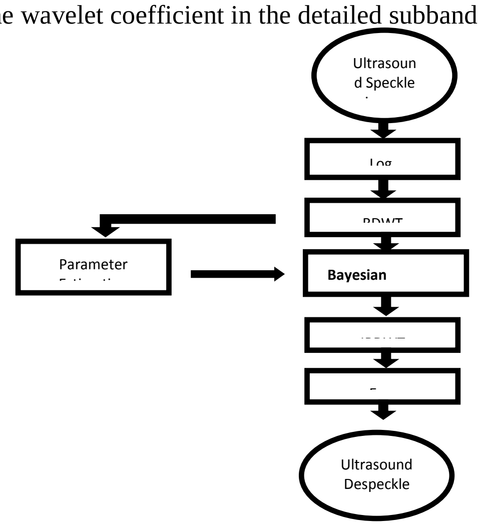

Fig 3: Block diagram show proposed despeckling algorithm

5.2 Estimation of noise variances σ^2_N :

The parameter noise variances σ^2_N needs to be estimated first [11]. It may be possible to measures σ^2_N based on information other than the corrupted image and it is estimated from the subband HH_1 by the robust median estimator, [4] Donoho proposed a formula to estimate the noise variance for additive noise model in the wavelet domain as

$$\sigma^2_N=\left[\frac{median\ (|y\ l|)}{0.6745}\right]^2, Y_l \varepsilon (HH_1) \text{ ………………………………………..… (17)}$$

Correlation properties of the speckle have an effect on the wavelet decompositions up to a scale that corresponds to its granular size. They suggested that the noise variance, σ^2_N should be estimated from

$$\sigma^2_N=\left[\gamma \frac{median\ (|y\ l|)}{0.6745}\right]^2, Y_l\ \varepsilon (HH_{1,}\ HH_2) \text{…………………………………... (18)}$$

Where, γ is a tuning parameter introduced to control the degree of smoothness of the denoised output. The proposed method uses equation (17) to estimate $\sigma^2_{N.}$

5.3 Estimation of Generalized Gamma Distribution Parameters:

The estimation of the parameters of the GGAD is done by using the MLE procedure. This method does not require the computation of derivatives but requires an initial guess of the solution. The initial guesses of the parameters (denoted with subscript 0 in this paper) were obtained using the method of moments as described in [11]. For the GGAD, the initial parameters, namely K, and ϴ, are computed from the wavelet coefficients of the diagonal detail sub-bands (HH_1, HH_2) using following equations (19), and (20), respectively.

$$\frac{\Psi''(K)}{\Psi'(K)^{1.5}}=\left|\frac{[(\ln(\gamma))-\ln(\gamma)^3]}{\{E[\ln(\gamma)-\ln(\gamma)^2]\}^{1.5}}\right| \text{ …………………………………………(19)}$$

$$\Theta = \frac{\Gamma(K)}{\Gamma(K+\frac{1}{K})} \text{ …………………………………………… (20)}$$

Where, $\Psi'(K)$ and $\Psi''(K)$ represent the first and second derivatives with respect to K, respectively, and $\Psi(K)= \frac{dy}{dx}\ln(\Gamma(K))$ is the digamma function. The value of K can be obtained by using the Gauss-Newton method. After K was obtained, subsequently the value of ϴ was obtained using (20).

V. SPECKLE SIMULATION PROCEDURE

However, practically this does not put any constraint to the use of the proposed method. For example, for a 256 × 256 US image corrupted by artificial speckle, it takes approximately 4 seconds for the proposed optimal parameter estimation [10]. We use the MATLAB function cputime to measure the computational complexity.

VI. EXPERIMENTAL RESULT AND DISCUSSIONS

We tested our proposed Bayesian speckle suppressing algorithm on the ultrasound images. In order to obtain speckle images, we degraded the original test images by multiplying them with unit-mean random fields. We compared the results of our approach with soft thresholding speckle reduction technique.

In order to quantify the achieved performance improvement, for quantitative evaluation, an extensively used measure is the MSE defined as Mean-square error (MSE)

For quantitative evaluation [10], an extensively used measure is the MSE defined as

1) Mean-square error (MSE)

$$\text{MES} = \frac{1}{M}\sum_{i=1}^{M}\left(g_i^{\wedge} - g_i\right)^2 \text{ ………...…..... (21)}$$

Where, M, g_i, and $g_i^{\wedge}$ are size of the original image, and denoised image, respectively.

2) Signal-to-MSE (S/MSE) ratio [10]

The larger S/MSE values correspond to better image quality. Coherent imaging is to calculate the signal-to-MSE (S/MSE) ratio, defined as

$$\text{S/MES} = 10 \times \log_{10}\left(\frac{\sum_{i=1}^{M} g_i^2}{\sum_{i=1}^{M}(g_i^{\hat{}} - g_i)^2}\right) \qquad (22)$$

3) Speckle-signal-to-noise ratio (SSNR) [5]

It is defined as the ratio of mean to the standard deviation of the speckled image. Its reciprocal is called of speckle contrast. Therefore, a lower value of SSNR corresponds to better contrast.

$$\text{SSNR} = \frac{\text{mean of the image}}{\text{standard deviation of the image}} \qquad (23)$$

4) Edge-preservation index (β) [11, 12]

$$\beta = \frac{\Gamma\left(\Delta g - \overline{\Delta g}, \Delta g^{\hat{}} - \overline{\Delta g^{\hat{}}}\right)}{\sqrt{\Gamma\left(\Delta g - \overline{\Delta g}, \Delta g - \overline{\Delta g}\right) - \Gamma\left(\Delta g^{\hat{}} - \overline{\Delta g^{\hat{}}}, \Delta g^{\hat{}} - \overline{\Delta g^{\hat{}}}\right)}} \qquad (24)$$

Where, $g$and $g^{\hat{}}$ are the high-pass–filtered versions of $g$and $g^{\hat{}}$, respectively, obtained with a 3×3 pixel standard approximation of the Laplacian operator and

$$\Gamma(g_1, g_2) = \sum_{i=1}^{M} g_1 . g_2 \qquad (25)$$

The edge-preservation index β should be close to unity for an optimal effect of edge preservation.

5) Coefficient of correlation (α) [10]

$$\alpha = \frac{\Gamma\left(g - \overline{g}, g^{\hat{}} - \overline{g^{\hat{}}}\right)}{\sqrt{\Gamma\left(g - \overline{g}, g - \overline{g}\right) \Gamma\left(g^{\hat{}} - \overline{g^{\hat{}}}, g^{\hat{}} - \overline{g^{\hat{}}}\right)}} \qquad (26)$$

Where, $g$and $g^{\hat{}}$ are the original and thedespeckled images, respectively. It is the measure of similarity between the ground truth image and despeckled image. Ideally, coefficient of correlation α should be close to unity.

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VII. FIGURES AND TABLES

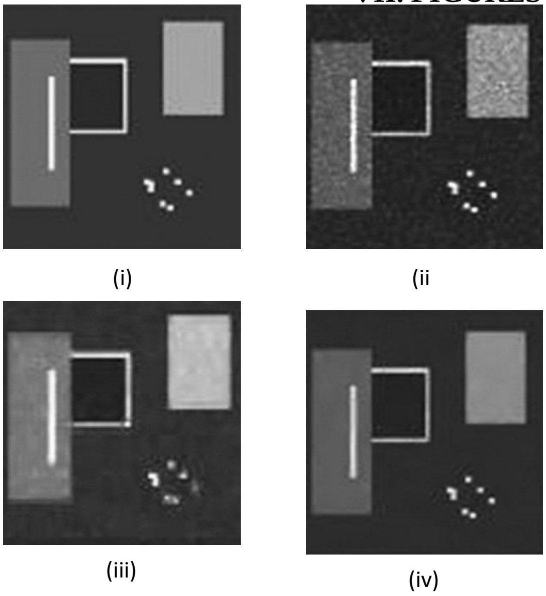

Fig 4; (i) Speckle image (ii) Speckle simulated
(iii) Soft threshoding (iv) Proposed method

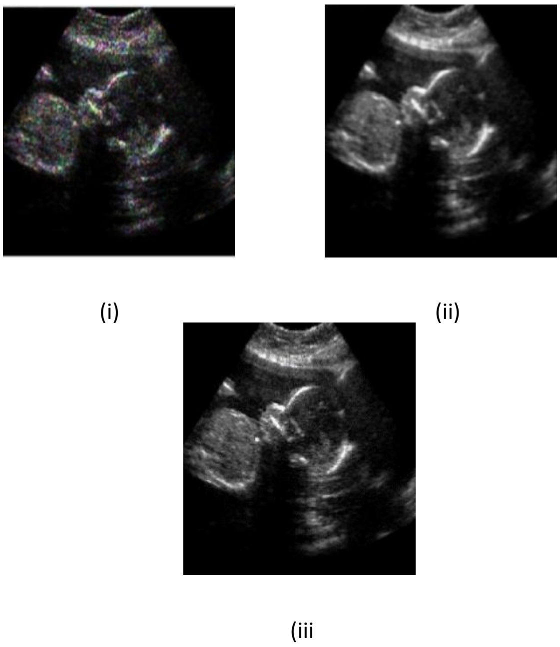

Fig 5: (i) Speckle image (ii) Soft threshoding
(iii) Proposed method

Method	I/P (SSNR)/ (S/MSE)	Output SSNR	S/MSE	β	α
Without Filtering	1.374 /11.405	1.4686	16.455	0.509	0.965
Soft Threshold-ing		1.4192	17.846	0.794	0.975
Bayesian Denoising		1.5176	17.771	0.822	0.977

I/N- Input, SSNR – Speckle-signal-to-noise ratio; MSE Mean-square error
Table 1: Image quality measures obtained by various denoising methods tested on two 128×128 real US test images (img1 and img2 in Figures 2 and 5 , respectively) at two input noise levels (i.e., σ = 0.7 and σ = 0.8 respectively) and with γ =1. The S/MSE is given in dB and the other parameters (SSNR, β, α) are the unit-less quantities

VIII. CONCLUSIONS

In this paper, we introduced a novel approach of speckle noise in ultrasound imaging using redundant discrete wavelet transform method for speckle suppression in ultrasound images. The main advantage of our method is that the obtained I/O shrinkage functions are optimal in the Bayesian sense.

The significant feature provided by the GGAD model is its versatility to different types of US images. To adapt the estimator to the local image statistics, signal variance is estimated from the local neighbourhood.

We also have demonstrated the performance superiority of the proposed algorithm over well-known spatial domain filters and state-of-the-art wavelet-based denoising techniques in terms of different quantitative techniques, such as SSNR, S/MSE, and edge preservation index.

IX. ACKNOWLEDGEMENT

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