Performance Evaluation of Various Filters for Reducing Speckle Noise in Ultrasound Images

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Abstract—Ultrasound imaging is used for early detection of abnormality of fetus. Speckle noise is considered as a primary source of medical ultrasound imaging noise and it must be filtered out. Several approaches are there for noise reduction. Filtering is one of the medical image processing techniques for noise reduction. In this paper a study of various filtering techniques for removal of speckle noise from ultrasound images is done. Despeckling improves the quality of the ultrasound images.

Keywords—Ultrasound imaging; Speckle noise; Filtering; Despeckling.

I. INTRODUCTION

Ultrasonography is the most widely used pregnancy observation method because it is relatively cheap and noninvasive. Ultrasound Speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with small particles or objects on a scale comparable to the sound wavelength. Speckle is an inherent property of an ultrasound image, and is modeled as spatial correlated multiplicative noise [1]. Noise is introduced at all stages of Image acquisition. The speckle noise degrades the fine details and edge definition and limits the contrast resolution by making it difficult to detect small and low contrast organ or tissue in body.

Speckle may appear distinct in different imaging systems but it is always represented in granular pattern due to image formation under coherent waves [2][3]. Speckle reduction is a critical pre-processing step for extraction of features, analysis and recognition from medical ultrasound image measurements.

Commonly used linear low-pass filters, such as the mean filters, are not suitable for reducing the speckle noise of ultrasound images since they eliminate the high frequencies and, thus, tend to smooth out the image edges.

The rest of the paper is organized as follows: Section II presents the Model of Speckle noise. Section III presents a survey of various despeckling filters for Ultrasound images. Section IV illustrates various parameters used for analyzing the performance of Despeckling Filters. Finally our conclusions are presented in Section V.

II. MODEL OF SPECKLE NOISE

Speckle is not a noise in an image but noise-like variation in contrast. It is due to the random variations in the strength of the backscattered waves from objects and is usually seen in RADAR and Ultrasound images. A speckle noise is defined as multiplicative noise, with a granular pattern.

Speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. Speckle degrades the quality of ultrasound images and reduces the ability of a human observer to discriminate the fine details of diagnostic examination.

The Simplified model of the speckle for ultrasound image [4][5] is represented as,

$$g(n,m) = f(n,m) * u(n,m) \qquad (1)$$

where, g(n,m) is the observed image and u(n,m) is the multiplicative component of the speckle noise. Here n and m denotes the axial and lateral indices of the image samples.

III. SPECKLE REDUCING FILTERS FOR ULTRASOUND IMAGES

A. Non Local – means Filter with Maximum likelihood Estimator.

Non-Local Means (NL-means) filter removes noise and enhances edge information [6]. Y.Guo *et al*. proposed Modified Non Local-based (MNL) filter [7] to adapt for the speckle reduction with the Rayleigh distribution noise. The MNL method consists of two steps. The maximum likelihood (ML) estimation to calculate the initial noise-free intensity is done first. Then, the NL-means algorithm is used to restore details. The ML estimator does not retain fine structure details and usually makes edge blurred. MNL speckle filter includes ML estimator and NL-means filter.

1) ML estimator:

For each pixel i in the noise image g,

(a) take the window Δi , which is defined as the neighborhood of pixel i and Mi which is defined as a square neighborhood of pixel i;

(b) compare the average intensity in Δi to discard unwanted ones;

(c) compute the initial noise-free value f ML(i) using

$$f(i) = \hat{\sigma}_g\,(\sigma_\eta)^{-1} = \left[\left(\frac{1}{2\pi(\sigma_\eta)^2}\right) . \sum_{k=1}^{n} g^2\,(i_k)\right]^{1/2} \quad (2)$$

where g i is a noisy pixel, $\sigma\eta$ is the shape parameter.

2) NL-means filter:

For each pixel i in the ML filtered image f ML,

(a) take the search window Ωi and the neighborhood window Ni;

(b) for each pixel j in the search window, compute d(i, j), Z(i) and w(i, j).

$$d(i, j) = G_\rho \left\| g(N_i) - g(N_j) \right\|^2 \quad (3)$$

where Gp is a normalized Gaussian weighted function with zero mean and p standard deviation. Then, w(i, j) is calculated as,

$$w(i, j) = \left(\frac{1}{Z(i)}\right) . \exp\left(\frac{-d(i,j)}{h^2}\right) \quad (4)$$

$$Z(i) = \sum_{j \in 1} \exp\left(\frac{-d(i,j)}{h^2}\right) \quad (5)$$

Here Z(i) is the normalized constant. The parameter h acts as a degree of filtering.

(c) Given a discrete noisy image g ={g(i)|i I}, the filtered value NL(g(i)) is calculated as a weighted average of all pixels in the image.

$$NL(g(i)) = \sum_{j \in 1} w(i, j) g(i) \quad (6)$$

To evaluate the performance of the MNL, Y.Guo et al [7] optimized three parameters of the MNL and tested it on synthetic images and clinical ultrasonic images. The three optimized parameters are h (decay of exponential function), radius of similar neighbourhood and radius of search window. The MNL performance was compared with six other filters namely NL-means filter, ML estimator, Lee filter, Median filter, SRAD and Med-wavelet filter. The MNL can preserve more true edges, discarding the false ones. It suppresses the speckle in ultrasonic images. Since the MNL filter makes use of the image redundancy, it is time-consuming in 2-dimensional case.

B. Squeeze Box Filter (SBF) for Contrast Enhancement

Peter et al [8] developed a method in which the contrast enhancement is with respect to decreasing pixel variations in homogeneous regions while maintaining or improving differences in mean values of distinct regions. The smoothing parameter k determines the degree or amount of smoothing and is derived from some function of the local statistics. This parameter takes any continuous value between zero and one.

The smoothing should occur when the pixel is within a homogeneous region and the local mean should be the mean determined from this homogeneous region. If the pixel value lies on an edge due to some significant anatomical feature of interest, then the original pixel value should be preserved. The SBF method aims at removing outliers. By removing outliers at each iteration, this method reduces the local variance of the signal or image. It produces a converging sequence of signals or images by squeezing or compressing the stochastically distributed pixel values to some limiting value. Since the proposed filtering method is able to compress the distribution of pixel values, it is named the squeeze box filter (SBF).

The proposed work by Peter et al [8] was carried out with the Mathworks MatLab® Field II simulation version 3.16 which simulates a B-mode ultrasound image of template from a linear array. Better despeckling results are achieved with the SBF method than with the other tested methods. The SBF method replaces the outliers with the local mean. The quantitative results showed that the SBF method consistently and more often provided contours that better resembled the manually defined contours.

C. Quantum – Inspired adaptive threshold Method

On the basis of principles of quantum signal processing (QSP) [9], a despeckling method based on a quantum-inspired adaptive threshold function is proposed by Fu et al [10]. The algorithm is summarised as:

1. Determine the log-transformation of the speckled ultrasound image.
2. Decompose the log-transformed noisy image Y using DTCWT.
3. Calculate the noise variance using the equation

$$\hat{\sigma}_n = \text{median}\left(\left|Y_r^{45^\circ}\right|\right) \Big/ 0.6745 \qquad (7)$$

Where $Y_r^{45^\circ}$ denotes the real component of 45° direction subband wavelet coefficients at the finest scale.

4. Shrink complex wavelet coefficients based on the quantum-inspired adaptive threshold function:
   a) Estimate σ using the equation,

$$\hat{\sigma} = \sqrt{\left(\frac{1}{M}\sum_{(m,n)\epsilon W(i,j)} |Y(s,m,n)|^2 - \sigma_n^2\right)_+} \qquad (8)$$

where |Y(s, m, n)| denotes the modulus of complex wavelet coefficient Y(m, n) at the s th scale and M is the size of neighbourhood W(i, j).

   b) Estimate K using the equation,

$$K = k_0 + \cos^2\left(NC_{smn} \times \frac{\pi}{2}\right) \qquad (9)$$

where k_0 is a tunable parameter determined by the histogram of noise free signal complex coefficients X.

   c) Update each coefficient using the equation,

$$\hat{X} = \frac{\left(\sqrt{Y_r^2+Y_i^2} - \sqrt{3}\exp(K)\sigma_n^2/\sigma\right)_+}{\sqrt{Y_r^2+Y_i^2}} \times Y \qquad (10)$$

Apply the inverse DTCWT to the estimated coefficients.

5. To obtain the despeckled image, take the exponential transformation.

The Quantum – Inspired adaptive threshold Method not only gives good performance in terms of SNR, but also has a better edge preservation capacity. Furthermore, the subjective image quality by the approach is much better than the other related methods in image details preservation and speckle suppression.

D. Function Spaces approach

In function spaces approach, Speckle noise is suppressed without smearing the edges, by extending the smoothness of the image in the wavelet-based Holder spaces [11]. It is a new wavelet shrinkage technique for speckle reduction and edge preservation. This is done by adjusting the wavelet coefficients according to wavelet decomposition level. Lee et al [11] evaluates the denoising of speckle noise based on three experiments: two synthetic images and real ultrasound image. The speckle reduction scheme is accomplished by tuning the detail wavelet coefficients that are related to the smoothness of the image. The denoising scheme of Function Spaces Approach is implemented in three steps:

(1)The noisy image is decomposed into the coarse scale approximation and detail images by a three-level 2D DWT.

(2) The detail wavelet coefficients d_i^{HH}, d_i^{HL} and d_i^{LH} are regularized by 'smoothing factor' β as

$$\begin{cases} d_j^{HH+} = 2^{-j\beta}\, d_j^{HH} \\ d_j^{HL+} = 2^{-j\beta} d_j^{HL} \\ d_j^{LH+} = 2^{-j\beta} d_j^{LH} \end{cases} \quad j=1, 2 \text{ and } 3 \qquad (11)$$

(3) The denoised image is reconstructed by taking the inverse DWT of the wavelet shrinking coefficients.

The function spaces approach algorithm illustrates two advantages over general wavelet shrinkage denoising methods. First, the speckle statistics of the noisy image is not exploited. Second, the detail wavelet coefficients are adjusted without setting up the threshold function.

The experimental results of function spaces approach [11] shows efficiency in smoothing speckle noises and preserving edge structures. A 2D phantom and a noise model available in MATLAB are considered for the experiment. The synthetic image 'Phantom' which is an 8 bit image of 256 × 256 pixels was corrupted with different levels of noise. Then, the MATLAB speckle simulation based on the following image model

$$u(x,y) = v(x,y) + v(x,y)sp(x,y) \qquad (12)$$
$$sp(x,y) \sim N(0, s2)$$

was applied to the 'Phantom' image, where u, v are the noisy and ideal images, respectively. Three levels of speckle noise were tested by setting σ = {0.2, 0.4, 0.8}.

Speckle deduction was implemented according to the equation (11) and the smoothing factor β was chosen from 1, 2, up to 7. The test conducted by Lee et al results show that the difference of quantitative measure among different smoothing factors is very small (less than 0.02). In comparing both the visual and numerical results, the Function Spaces Approach smoothed out the speckles successfully and obtained the best edge preservation performance.

E. Coherent Filtering

Coherent Filtering is a despeckling technique based on Coherent Anisotropic Diffusion [12]. The steps involved in Coherent Filtering are:

1. Construct Multiplicative noise model.
2. Perform transformation of Multiplicative noise model.
3. Determine Wavelet transform of noisy image.
4. Calculate variance of noise.
5. Calculate weighted variance of signal ∂.
6. Calculate threshold value λ of all pixels and sub band coefficients.
7. Take inverse DWT to do despeckling of Ultrasound images.

Milindkumar et al [12] carried out denoising for ultrasound image with speckle noise of variance σ2=0.03, 0.04, 0.05, using standard speckle filters and coherent filter. Since the coherent filter model automatically collects the information about noise variance, the images are denoised and enhanced.

F. Bayesian Non-Local means based filter

Coupe et al [14] proposed an adapted method based on Bayesian formulation of non-local means filter for speckle noise reduction. To reduce the computational complexity of the algorithm, a blockwise approach is introduced in which a weighted average of patches is performed instead of weighted average of pixel intensities. This approach includes the following:

1) Paritioning the image Ω into overlapping blocks B_{ik} of size $P=(2\alpha+1)^d$ (d is the dimensionality of image) such as $\Omega=U_kB_{ik}$.

2) Restoration of a block B_{ik} based on a non-local means scheme defined as

$$NL(u)(B_{ik}) = \sum_{B_j \epsilon V_{ik}} w(x_{ik}, x_j) u(B_j) \qquad (13)$$

$$w(x_{ik}, x_j) = \frac{1}{Z_{ik}} e^{-\frac{\|u(B_{ik})-u(B_j)\|_2^2}{h^2}} \qquad (14)$$

where $u(B_i) = \left(u^{(1)}(B_i), \ldots, u^{(P)}(B_i)\right)^T$ is an image patch containing the intensities of the block B_i, Z_{ik} is a normalization constant.

3) Restoring the pixels values based on the restored intensities of the blocks they belong to. The final restored intensity of pixel x_i is defined as

$$NL(u)(x_i) = \frac{1}{|A_i|} \sum_{i \epsilon A_i} A_i\,(l) \qquad (15)$$

Based on Bayesian interpretation of the non-local means filter [15], the blockwise NL means can be written as

$$NL(u)(B_{ik}) = \frac{\frac{1}{|V_{ik}|} \sum_{j=1}^{|V_{ik}|} p(u(B_{ik})|u(B_j))p(u(B_j))u(B_j)}{\frac{1}{|V_{ik}|} \sum_{j=1}^{|V_{ik}|} p(u(B_{ik})|u(B_j))p(u(B_j))} \qquad (16)$$

where $p(u(B_{ik})|u(B_j))$ and $p(u(B_j))$ respectively denote the distribution of $u(B_{ik})|u(B_j)$ and the prior distribution of patches.

Evaluations were performed on synthetic data with different noise levels and different speckle simulations [14]. Experiments [14] shows that the filter outperforms the classical implementation of the NL means filter as well as SRAD (Speckle Reducing Anisotropic Diffusion)and the SBF (Squeeze Box Filter).

IV. Parameters Used For Performance Analysis Of Despeckling Filters

To determine the performance of despeckle filters in terms of efficiency of removal of speckle noise and enhancement of useful image information, the following parameters are analyzed. Table I provides the metrics [13] used for performance analysis.

Table I - Parameters for analysis of performance of despeckle filters

Despeckle filter	Performance metrics used	Range of Value for Better performance	Range of values of despeckling filter
Non Local – means Filter with Maximum likelihood Estimator [7]	**Signal-to-Noise Ratio (SNR)**	**Higher values show better image quality**	**Under different noise conditions the values for MNL filter ranges from 18-20**
	Mean Structure Similarity (MSSIM)	**Closer to unity for optimal measure of similarity**	**0.884 to 0.961**
	Figure of Merit (FOM)	**Closer to unity for optimal measure of similarity**	**0.753 to 0.915**
Squeeze Box Filter (SBF) for Contrast Enhancement [8]	**Mean Structure Similarity (MSSIM)**	**Closer to unity for optimal measure of similarity**	**0.8432**
	Ultrasound Despeckling Assessment Index (USDSAI)	**Larger values indicate better performance**	**4.0291 for SBF and 1to 3 for other filters**
Quantum-Inspired adaptive threshold Method [10]	**Signal-to-Noise Ratio (SNR)**	**Higher values show better image quality**	**16.40**
Function Spaces approach [11]	**Mean Structure Similarity (MSSIM)**	**Closer to unity for optimal measure of similarity**	**0.7701 to 0.7805**
	Figure of Merit (FOM)	**Closer to unity for optimal measure of similarity**	**0.6734 to 0.8326**
Coherent Filtering [12]	**Peak Signal to Noise Ratio (PSNR)**	**Higher values show better image quality**	**27.695 to 32.614**
Bayesian Non-local means based filter [14]	**Signal-to-Noise Ratio (SNR)**	**Higher values show better image quality**	**42.13 to 64.13**

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Although all speckle filters perform well on ultrasound images they have some constraints regarding resolution degradation. Non-Local Means (NL-means) filter removes noise and enhance edge information. The MNL can preserve more true edges, discarding the false ones. It suppresses the speckle in ultrasonic images. Since the MNL filter makes use of the image redundancy, it is time-consuming in 2-dimensional case.

In Squeeze Box Filter (SBF) method the contrast enhancement is with respect to decreasing pixel variations in homogeneous regions while maintaining or improving differences in mean values of distinct regions. The Quantum – Inspired adaptive threshold Method not only gives good performance in terms of SNR, but also has a better edge preservation capacity. The subjective image quality by the approach is much better than the other related methods in image details preservation and speckle suppression.

In function spaces approach, Speckle noise is suppressed without smearing the edges, by extending the smoothness of the image in the wavelet-based Holder spaces. The coherent filter model automatically collect the information about noise variance, the images are denoised and enhanced. The Bayesian Non-local means algorithm reduces the computational complexity of the algorithm used for filtering.

VI. References

[1] Yong Yue, Mihai M. Croitoru, Akhil Bidani, Joseph B. Zwischenberger and John W. Clark, " Nonlinear multiscale diffusion for speckle suppression and edge enhancement in ultrasound images", IEEE Transactions on Medical Imaging, Vol.25 ,No.3,pp. 297 – 311,Mar 2006.

[2] J. Goodman, "Some fundamental properties of speckle", Journal of the Optical Society of America, Vol 66, pp.1145-1150,Nov 1976.

[3] Anil K.Jain, "Fundamental of digital image processing", Prentice Hall, 1989.

[4] K.Thangavel, R. Manavalan, Laurence Aroquiaraj, "Removal of speckle noise from ultrasound medical image based on special filters : Comparative Study", ICGST – GVIP Journal, Vol.9, Issue : 3, June 2009.

[5] Milindkumar V. Sarode and Prashant R. Deshmukh, "Reduction of speckle noise and image enhancement of images using filtering technique", International Journal of Advancements in Technology, Vol 2, No.1, Jan 2011.

[6] A. Buades, B. Coll, J.M. Morel, "A review of image denoising algorithms, with a new one, Multiscale Modelling & Simulation, Vol. 4, Issue 2, pp. 490–530.,2005.

[7] Y.Guo, Y.Wang, T.Hou, "Speckle filtering of ultrasonic images using a modiified non local-based algorithm", Biomedical Signal Processing and Control, Elsevier, pp. 129 – 138, 2011.

[8] Peter C. Tay, Christopher D. Garson, Scott T. Acton and John A. Hossack, "Ultrasound despeckling for contrast enhancement", IEEE Transactions on Image Processing, Vol 19, No. 17, Jul 2010.

[9] Eldar, Y.C., and Oppenheim, A.V,"Quantum signal processing", IEEE Signal Process. Mag., 2002, pp. 12–32.

[10] X.W.Fu,M.Y.Ding and C.Cai, "Despeckling of medical ultrasound images based on quantum- inspired adaptive threshold",Electronics Letters, Vol.46, No.13,Jun 2010.

[11] M.S.Lee,C.L.Yen,S.K.Ueng, " Speckle reduction with edges preservation for ultrasound images : using function spaces approach", IET Image Processing, Vol.6, Iss.7, pp.813-821, 2012.

[12] Milindkumar V. Sarode, Prashant R. Deshmukh, " Reduction of speckle noise and image enhancement of images using filtering technique", International Journal of Advancements in Technology, Vol.2, No.1, Jan 2012.

[13] R.Sivakumar, M.K.Gayathri and D.Nedumaran, "Speckle filtering of ultrasound B-Scan images – A comparative study between spatial and diffusion filters, 2010 IEEE conference on open systems (ICOS 2010),Kuala Lumpur, Malaysia, Dec 2010.

[14] Pierrick Coupe, Pierre Hellier, Charles Kervram and Christian Barillot, "Bayesian non local means-based speckle filtering",IEEE International Symposium on Biomedical Iamging,2008.

[15] C. Kervrann, J. Boulanger, Pierrick Coupe, "Bayesian non-local means filter, image redundancy and adaptive dictionaries for noise removal", SSVM'07 Proc of the 1st International conference on scale space and variational methods in computer vision,2007, pp. 520-532.