Comparative Study on Speckle Noise Suppression Techniques for Ultrasound Images

S.Sudha, G.R.Suresh, R.Sukanesh

***Abstract*— In medical image processing, image denoising has become a very essential exercise all through the diagnose. Negotiation between the preservation of useful diagnostic information and noise suppression must be treasured in medical images. In certain cases, for instance in Ultrasound images, the noise can restrain information which is valuable for the general practitioner. The success of ultrasonic examination depends on the Image quality. In case of ultrasonic images a special type of acoustic noise, technically known as speckle noise, is the major factor of image quality degradation. Many denoising techniques have been proposed for effective suppression of speckle noise. This paper presents the performance analysis of various schemes for suppressing speckle noise in Ultrasound images in terms of the assessment parameters PSNR and Equivalent Number of Looks (ENL).**

***Index Terms*—Medical image processing, image enhancement, ultrasonic imaging, speckle noise, ultrasound speckle reduction, speckle filtering.**

I. INTRODUCTION

Unlike many other imaging applications, where the quality of the denoised image is estimated by how pleasant visual interceptions it gives to the human eye, medical applications require some constraints, for example the generation of artifact that could be misinterpreted as clinically interesting features. To achieve the best possible diagnoses it is important that medical images be sharp, clear, and free of noise and artifacts. While the technologies for acquiring digital medical images continue to improve, resulting in images of higher and higher resolution and quality, noise remains an issue for many medical images. Removing noise in these images remains one of the major challenges in the study of medical imaging. This paper stresses the importance of such situations and devises some requirements that should be met in order to be of better assistance in real clinical analysis.

A. Ultrasonography

It is an ultrasound-based medical imaging technique used to visualize muscles and many internal organs, their size, structure and any pathological injuries with real time tomographic images. It is also used to visualize a fetus during routine and emergency prenatal care. Obstetric sonography is commonly used during pregnancy. The technology is relatively inexpensive and portable, especially when compared with other imaging techniques such as magnetic resonance imaging (MRI) and computerized tomography (CT). It has no known long-term side effects and rarely causes any discomfort to the patient. Small, easily carried scanners are available; examinations can be performed at the bedside. Since it does not use ionizing radiation, ultrasound yields no risks to the patient. It provides live images, where the operator can select the most useful section for diagnosing thus facilitating quick diagnoses.

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B. Speckle noise

Ultrasound images are corrupted by speckle noise that affects all coherent imaging systems. Within each resolution cell a number of elementary scatters reflect the incident wave towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern that delays the interpretation of the image content and reduces detectability of the features of interest. In medical literature also referred to as "texture", may present useful diagnostic information. It is therefore advantageous to provide a user interactive denoising method, where the degree of speckle smoothing can be tuned.

A speckled image $V = \{v_1, v_2, v_3 ......v_n\}$ is commonly modeled as $v_1 = f_1 J$ where $f = \{f_1, f_2, f_3, ... f_n\}$ is a noise-free ideal image, and $J = \{J_1, J_2, ...J_n\}$ is a unit mean random field.

The organization of this paper is as follows: In section II various standard speckle filters and other denoising methods are explained. Wavelet filters, Wavelet thresholding procedure are described in section III. Simulation results of various noise reduction techniques are presented in section IV. Section V illustrates the results and discussion of various denoising techniques.

II. STANDARD SPECKLE FILTERS

Physicians generally prefer the original noisy images more than the filtered one because the filters even if they are more sophisticated can destroy some relevant image details. Thus it is essential to develop noise filters which can secure the preservation of those features that are of interest to the physician. This section explains about some of the best known standard speckle filters.These filters use the second-order sample statistics within a minimum mean squared error estimation approach. Other filters such as Oddy [11], texture-preserving filter and ASF are less familiar due to their algorithmic complexity [14]. Although all these filters perform well on images it has some constraints regarding resolution degradation [14]. There are also other filters less frequently used, such as Kalman filter [17], Geometric filter [16], the adaptive (LMMSE) filter [18], and Weighting filter [15].

A. *Frost filter*

Frost filter [9] is a spatial domain adaptive Wiener filter that is based on the multiplicative noise model and uses the local statistics. The image $Z[i, j]$ is modeled by frost as

$$Z_{i,j} = \lfloor X_{i,j}.n_{i,j} \rfloor * h_{i,j} \qquad \text{----------- (2.1.1)}$$

Where $h_{i,j}$ is system impulse response and * denotes convolution. Minimum mean square filter has the form

$$\hat{x}(t) = z(t) * m(t) \tag{1}$$

Where $t = (i, j)$ is the spatial coordinate. The ***m (t)*** function is an isotropic impulse response of the spatial filter chosen to minimize

$$J = E[\hat{x}(t) - x(t)]^2 \tag{2}$$

It is given by the expression:

$$m(t) = K_1 a \exp(-at) \tag{3}$$

K_1 is a normalizing constant and α is the decay constant given by:

$$a^2 = 2a \Big/ s_n^2 \left[\frac{s_x^2}{s_x^2 + \bar{z}^2} \right] + a \tag{4}$$

Where ***a*** the correlation coefficient between adjacent pixels of the original is image ***x(t)*** and $|t|$ corresponds to the distance between pixels in the spatial domain.

B. *Kaun filter*

Kaun filter [8] is a local linear minimum square error filter based on the multiplicative model. To perform the adaptive speckle noise point wise filtering, local statistics are computed using a fixed neighborhood. Noisy pixel is updated by the expression:

$$\hat{x} = m_x + K(z - m_x) \tag{5}$$

Where $\hat{x}$ is minimum mean square estimate of x, $\boldsymbol{\mu_x}$ is obtained from the local mean of the noisy pixel computed in the fixed neighborhood, ***z*** is the noisy pixel and K is given by:

$$K = \frac{s_x^2}{s_n^2 m_z^2 + (1 + s_n^2) s_x^2} \tag{6}$$

In the absence of a precise model for the signal ***x***, the noisy image is used to estimate the Apriori mean and variance of the signal from the local mean, ***z*** and local variance ***σ***.

$$s_x^2 = \frac{s_z^2 - s_n^2 \bar{z}^2}{1 + s_n^2} \tag{7}$$

Where $\boldsymbol{\sigma^2_n}$ represents the noise variance and ***σ*** is the variance of the original image.

C. *Lee filter*

Lee filter [6], [7] is a particular form of Kaun filter. Lee filter is based on the multiplicative speckle model, and it can use local statistics to effectively preserve edges and features. Lee filter assume Gaussian distribution for speckle noise. Lee filter can be described by

$$W(t) = [1 - C^2_U / C^2_I] \tag{8}$$

Where $\boldsymbol{P_i}$ is the pixel's grey value within the filter window.

D. *Gamma Filter*

Gamma filter [10] is a Maximum A Posteriori (MAP) filter based on the Bayesian analysis of the image statistics. It assumes the speckle noise as Gamma distributed. The estimate is given by

$$\hat{x} = \frac{(a - L - 1)\bar{y} + \sqrt{\bar{y}^2 (a - L - 1)^2 + 4aLy\bar{y}}}{2a} \tag{9}$$

where

$$a = \frac{L + 1}{L\left(s_y \big/ \bar{y} \right)^2 - 1} \tag{10}$$

E. *Oddy Filter*

Oddy filter [11] is a mean filter whose window size varies according to the local statistics. The estimate is given by

$$\hat{x} = \bar{y} \quad \text{if } m < a\bar{y}. \tag{11}$$

$$\hat{x} = \frac{\sum_k \sum_l W_{kl} y(k,l)}{\sum_k \sum_l W_{kl}} \quad \text{if } m > a\bar{y} \tag{12}$$

$$W_{kl} = 1 \text{ if } |y(k,l) - y \leq m| \quad \text{if } W_{kl} = 0 \quad \text{Otherwise} \tag{13}$$

F. *Median filter*

It is defined as the median of all pixels within a local region of an image. It performs much better than arithmetic mean filter in removing salt and pepper noise from an image and in preserving the spatial details contained within the image. This method is particularly effective when the noise pattern consists of strong, spike like components and the characteristic to be preserved is edge sharpness.

G. *Weiner filter*

Conventional despeckling approach uses the homomorphic Wiener filter. Wiener filter, also Known as Least Mean Square filter, is given by the following expression; H(u, v) is the degradation function(* indicates complex conjugate) and G (u, v) is the degraded image.Functions $S_f(u, v)$ and $S_n(u, v)$ are power spectra of the original image and the noise.Wiener filter assumes the noise and power spectra of the object a priori.

$$f(u,v)=\left[\frac{H(u.v)^*}{H(u,v)^2+\left[S_n(u,v)\big/S_f(u,v)\right]}\right]G(u,v) \quad (14)$$

III. WAVELET FILTERS

Recently there has been significant investigations in medical imaging area using wavelet transform as a tool for improving medical images from noisy data. Wavelet denoising attempts to remove noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides non redundant and unique representation of the signal. Several properties of wavelet transform, which make this representation attractive for denoising are, Multi resolution, Sparsity, Edge detection, Edge clustering.

A. .Wavelet Thresholding

Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One widespread method exploited for speckle reduction is wavelet thresholding procedure.Basic Procedure for all thresholding method is

1. Calculate DWT of the image.
2. Threshold the wavelet coefficients.
3. Compute IDWT to obtain denoised Estimate.

There are two thresholding functions frequently used, i.e. Hard threshold, Pan *et al.* [4], Soft threshold. Hard-thresholding function keeps the input if it is larger than the threshold; otherwise, it is set to zero. Soft-thresholding function takes the argument and shrinks it toward zero by the threshold.Soft-thresholding rule is chosen over hard-thresholding, for the soft-thresholding method yields more visually pleasant images over hard thresholding. A small threshold may yield a result close to the input, but the result may still be noisy. Large threshold alternatively, produces signal with large number of zero coefficients. This leads to a smooth signal. So much attention must be paid to select optimal threshold. *Achim et.al* [5], *Thitimajshima.P et.al* [19] suggested speckle reduction through wavelet transform based on Bayesian approach by means of the statistical models of both noise and signal. Wavelet-based denoising using Hidden Markov Trees, initially proposed by *Crouse, et. al*. [20], *Romberg, et.al* [21] has been quite successful, and gave rise to a number of other HMT-based schemes. They tried to model the dependencies among adjacent wavelet coefficients using the HMT and used the minimum mean-squared error (MMSE)-like estimators for suppressing the noise. Some of the wavelet shrinkages are as follows.

B. Universal Threshold:

Donoho in his work [1], [2] proposed ***Universal*** threshold (Visu shrink) that over-smooth images. Universal threshold $T = s\sqrt{2\log n}$, with *n* equal to size of the image, σ is noise variance. This was determined in an optimal context for soft thresholding with random Gaussian noise. This is easy to implement but provides a threshold level larger than with other decision criteria, resulting in smoother reconstructed data. This estimation does not allow for the content of the data, but only depends on the data size ***n***. Also threshold tends to be high for large values of ***M***, killing many signal coefficients along with the noise. Thus, the threshold does not adapt well to discontinuities in the signal.

C. Stein Unbiased Estimated of Risk (SURE):

The Universal threshold was later improved by *Donoho* [2] using the SURE threshold. It is sub band adaptive and is derived by minimizing Stein's unbiased risk estimator. Stein's result to get an unbiased estimate of the risk

$$E\left\|\hat{m}^{(t)}(x)-m^2\right\| \quad : \quad SURE \quad (t; \quad x) \quad =$$

$$d\,d-2\#\left\{i=|x_i| \;<T\right\}+\sum_{i=1}^{d}\min\left(|x_i,t|\right)^2 \quad (15)$$

For an observed vector *x* the threshold t^S is found *that* minimizes SURE (*t;x*), i.e.

t^S =*Arg min*$_t$ *SURE(t:x)* (16)

The above optimization is computationally straightforward.

D. Spatially Adaptive Threshold:

Later *Chang et al.* [3] proposed the ***Bayes Shrink scheme***. In *Bayes* Shrink it is determined that the threshold for each sub band assuming Generalized *Gaussians distribution (GGD).* The GGD is given by

$$GG_{sX,b}(x)=C(sx,b)\exp-\left[\;a(sx,b)|x|\;\right]^b \quad (17)$$

Where $-\infty \le \infty, b \ge 0$

$$a(sx,b)=s_X^{-1}\left[\frac{\Gamma(3/b)}{\Gamma(1/b)}\right]^{1/2} \quad (18)$$

The parameter σ_x is standard deviation and β is shape parameter. Assuming such a distribution for the wavelet coefficients, σ_x and β is estimated for each sub band threshold, then ***T*** was found which minimizes the *Bayesian Risk*, i.e.

$$t(T)=E\left(\hat{X}-X\right)^2=E_X E_{X/Y}\left(\hat{X}-X\right)^2 \quad (19)$$

Then optimal threshold ***T is*** given by

$$T^*(sx,b)=\arg Min(T) \quad (20)$$

This is a function of parameters σ_x and β since there is no closed form solution for T^*, numerical calculation is used to find its value that is given by

$$T=b\,\frac{s^2}{s_X} \quad (21)$$

Where σ^2 is the noise variance, σ_x is the signal standard deviation. The parameters σ_x and β need to be estimated to compute $T(\sigma_x)$ that is adaptive to different sub band characteristics. The noise variance σ^2 is estimated based on information other than the corrupted image and it is estimated from the sub band HH_1 by median estimator, Noise variance $\sigma^2 = \left[\frac{median\left|{}_{m,n}\right|}{0.6745}\right]^2$ (22)

σ_x Can be derived as $\sigma_X = \sqrt{\max\left(\sigma_Y^2 - \sigma^2, 0\right)}$ (23)

Where $\sigma_Y^2 = \frac{1}{n^2}\sum_{m,n=1}^{n} Y_{m,n}^2$

To summarize, Bayes Shrink performs soft thresholding, with the data-driven, sub band dependent Threshold

$$T = \frac{\hat{\sigma}^2}{\hat{\sigma}_x} \qquad (24)$$

IV. ASSESSMENT PARAMETERS

A. Equivalent Numbers of Looks (ENL)

One of the good approaches of estimating speckle noise level is to measure ENL over a uniform image region. Larger value of *ENL* corresponds to better suppression of speckle. The value of *ENL* also depends on the size of the tested region; theoretically a larger region will produces a higher *ENL* value than over a smaller region. Formula for the *ENL* calculation is

$$ENL = \frac{(NMV)^2}{(NSD)^2} \qquad (25)$$

Where NMV, NSD are *Noise mean Value, Noise Standard Deviation* respectively where

$$NMV = \frac{\sum_{r,c} I_d(r,c)}{R * C} \qquad (26)$$

$$NV = \frac{\sum_{r,c}\left(I_d(r,c) - NMV \right)^2}{R * C} \qquad (27)$$

$$NSD = \sqrt{NV}$$

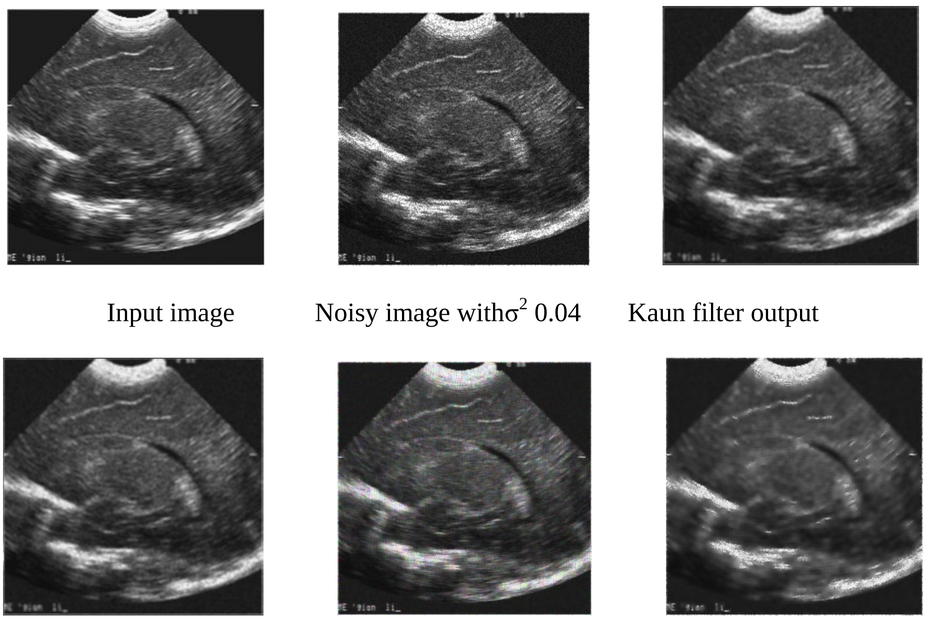
B. Deflection Ratio (DR)

Other performance estimator is the *Deflection Ratio*. The Deflection Ratio is given by

$$DR = \frac{1}{R * C}\sum\left[\frac{(I_d(r,c) - NMV)}{NSD} \right] \qquad (28)$$

The ratio *Deflection Ratio* should be higher at pixels with stronger reflector points and lower elsewhere.

V. SIMULATION RESULTS



Input image Noisy image withσ^2 0.04 Kaun filter output

Frost filter output Weiner filter output Bayes shrink output

Fig. 1: Noisy Ultrasound test image and denoised images of different filters.

TABLE 1: PERFORMANCE COMPARISON OF VARIOUS SPECKLE FILTERS, WAVELET FILTERS FOR ULTRASOUND IMAGE IN TERMS OF ENL

.Filter	ENL(Equivalent Number of looks)
Frost	15.643
Kaun	15.752
weiner	17.652
Visu shrink	20.274
Bayes shrink	23.309

TABLE 2: PERFORMANCE COMPARISON OF VARIOUS SPECKLES, WAVELET FILTERS FOR ULTRASOUND IMAGE IN TERMS OF PSNR.

σ^2	0.02	0.03	0.04	0.05	0.06	0.07
Frost	22.865	22.045	21.295	20.455	19.615	19.067
Kaun	22.685	22.027	21.583	20.845	20.016	19.126
Visu	31.741	30.823	29.946	28.418	27.221	26.012
Bayes	32.245	31.617	30.833	29.987	28.862	27.564
Weiner	30.274	29.627	28.732	27.637	26.836	25.912

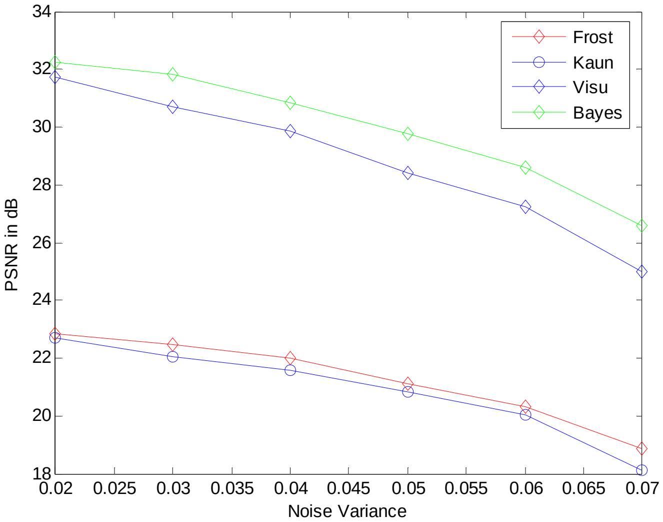


Fig 2: Comparison Chart of PSNR Vs Noise variance of different denoising methods for Ultrasound Image

VI. RESULTS AND DISCUSSIONS

The performance of the different denoising schemes is compared in Table 1 and Table 2. We have presented a comparative study of various wavelet filters and standard speckle filters for **U**ltrasound image in terms of *PSNR, ENL*. We have done all the simulations in *MATLAB* tool. All the wavelet-based techniques used *Daubechies 4* wavelet basis and 1 level of decomposition.Although all these speckle filters perform well on images it has some constraints regarding resolution degradation and are also less familiar due to their algorithmic complexity.These filters operate by smoothing over a fixed window, whose size is determined by two factors. In Homogeneous area large window size is needed to improve speckle reduction. But large window size reduces the resolution of the algorithm. When these filters attempt to reform a small bright object it produces artifacts around the object;that is the background is roughly defined in the neighborhood of bright edges. From Table1 and 2 it is clear that wavelet shrinkage filters are performed well than standard adaptive speckle filters. *VisuShrink* is the least effective among the methods compared. It over smooth the images. This is due to the fact that it is based on a Universal threshold and not sub band adaptive unlike the other schemes. Thus, the threshold does not adapt well to discontinuities in the signal. Among these, *BayesShrink* clearly performs the best. The *Sure Shrink* performed worse than *BayesShrink* but it adapts well to sharp discontinuities in the signal.

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