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Speckle Noise Reduction in Ultrasound Images by Wavelet Thresholding based on Weighted Variance

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

***Abstract*—In medical image processing, image denoising has become a very essential exercise all through the diagnose. Arbitration between the perpetuation of useful diagnostic information and noise suppression must be treasured in medical images. In general we rely on the intervention of a proficient to control the quality of processed images. In certain cases, for instance in Ultrasound images, the noise can restrain information which is valuable for the general practitioner. Consequently medical images are very inconsistent, and it is crucial to operate case to case. This paper presents a wavelet-based thresholding scheme for noise suppression in ultrasound images. Quantitative and qualitative comparisons of the results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction**

***Index Terms*—Medical imaging, Speckle noise, Ultrasound images, Wavelet Thresholding.**

I. Introduction

Medical images are usually corrupted by noise in its acquisition and Transmission. The main objective of Image denoising techniques is necessary to remove such noises while retaining as much as possible the important signal features. Introductory section offer brief idea about different available denoising schemes. Ultrasonic imaging is a widely used medical imaging procedure because it is economical, comparatively safe, transferable, and adaptable. Though, one of its main shortcomings is the poor quality of images, which are affected by speckle noise. The existence of speckle is unattractive since it disgrace image quality and it affects the tasks of individual interpretation and diagnosis. Accordingly, speckle filtering is a central pre-processing step for feature extraction, analysis, and recognition from medical imagery measurements. Previously a number of schemes have been proposed for speckle mitigation.

An appropriate method for speckle reduction is one which enhances the signal to noise ratio while conserving the edges and lines in the image. Filtering techniques are used as preface action before segmentation and classification. On the whole speckle reduction can be divided roughly into two categories. The first one recovers the image by summing more than a few observations of the same object which suppose that no change or motion of the object happened during the reception of observations. Statistical filter like Weiner filter [1] adopted filtering in the spectral domain, but the classical Wiener filter is not adequate while it is designed primarily for additive noise suppression [2].To address the multiplicative nature of speckle noise, Jain developed a homomorphic approach, which by obtaining the logarithm of the image, translates the multiplicative noise into additive noise, and consequently applies the Wiener.

Adaptive filter takes a moving filter window and estimates the statistical information of all pixels' grey value, such as the local mean and the local variance. The central pixel's output value is dependent on the statistical information. Adaptive filters adapt themselves to the local texture information surrounding a central pixel in order to calculate a new pixel value. Adaptive filters generally incorporate the Kuan filter, Lee filter, Frost filter, Gamma MAP filters [3], [4], [5]. These filters made obvious their superiority measured up to low pass filters, since they have taken into account the local statistical properties of the image. Adaptive filters present much better than low-pass smoothing filters, in preservation of the image sharpness and details while suppressing the speckle noise [6]. In most natural images counting medical images, there in general exists a context models like Markov random fields, for example, wavelet-based denoising using Hidden Markov Tree has been quite successful, and it 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 like estimators for suppressing the noise [7], [8].

Recently many challenges have been made to reduce the speckle noise using wavelet transform as a multi-resolution image processing tool. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One widespread method exploited for speckle reduction is wavelet shrinkage. When multiplicative contamination is concerned; multiscale methods engage a preprocessing step consisting of a logarithmic transform to separate the noise from the original image. Then different wavelet shrinkage approaches are employed. The well-known technique of wavelet shrinkage Universal threshold (Visu shrink) that

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over-smooth images [9] [10][11].This threshold was later improved by minimizing Stein's unbiased risk estimator[12]. BayesShrink performs better than SureShrink in terms of MSE. The reconstruction using BayesShrink is smoother and more visually appealing than the one obtained using SureShrink. In the BayesShrink scheme the threshold is determined for each sub band by assuming a Generalized Gaussian Distribution (GGD) .Within each sub band the wavelet coefficients are modeled as random variables with generalized Gaussian Distributions. BayesShrink performs better than SureShrink in terms of MSE. The reconstruction using BayesShrink is smoother and more visually appealing than the one obtained using SureShrink [13], [14]. All these thresholds are based on orthogonal wavelets and uses soft; thresholding technique by which the input is shrunk to zero by an amount of threshold T. Later in hard thresholding techniques the input is preserved if it is greater than the threshold; otherwise it is set to zero[15].Through Bayesian approach speckle reduction through wavelet transform is realized by means of the statistical models of both noise and signal [16], [17]. A comparative study between wavelet coefficient shrinkage filter and several standard speckle filters that are largely used for speckle noise suppression shows that the wavelet-based approach is deployed among the best for speckle removal[18], [19].

In our work, we recommend a novel thresholding algorithm for denoising speckle in ultrasound with wavelets. We favor our approach by Bayes Shrinkage function. The statistical analysis process is exactly the same for all data sets. Carrying out the statistical test in the wavelet domain require an inverse wavelet transform.

The paper is organized as follows: Section I, depicts about Ultrasound images, speckle noise .Section II, briefly highlights the main features of wavelets and the wavelet decomposition and Wavelet thresholding technique is described. In section III an image adaptive threshold imposed on the wavelet coefficient is calculated to identify the significant structures. Denoising procedure is explained in section IV. Experimental results are given in Section V in comparison with some existing denoising schemes. Finally, Section VI concludes the paper.

II. SPECKLE NOISE IN ULTRASOUND IMAGES

It is an ultrasound-based diagnostic 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. It is one of the most widely used diagnostic tools in modern medicine. The technology is relatively inexpensive and portable, especially when compared with other imaging techniques such as magnetic resonance imaging (MRI) and computed 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. This work aims to suppress speckle in Ultrasound images.

Speckle noise affects all coherent imaging systems including medical ultrasound. Within each resolution cell a number of elementary scatterers 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, called speckle that delays the interpretation of the image content. A speckled image 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, $V = \{v_1, v_2, v_3 ...... v_n\}$ speckle noise and $J = \{J_1, J_2, ... J_n\}$ is a unit mean random field.

In the medical literature, speckle noise is referred as "texture", and may possibly contain useful diagnostic information. The desired grade of speckle smoothing preferably depends on the specialist's knowledge and on the application. For automatic segmentation, sustaining the sharpness of the boundaries between different image regions is usually preferred while smooth out the speckled texture. For visual interpretation, smoothing the texture may be less desirable.

Physicians generally have a preference of the original noisy images more willingly than the smoothed versions 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 conservation of those features that are of interest to the physician. The wavelet transform has recently entered the field of image denoising and it has firmly recognized its stand as a dominant denoising tool.

III. WAVELET DOMIN NOISE FILTERING

Recently there has been significant investigations in medical imaging area using the wavelet transform as a tool for improving medical images from noisy data. Wavelet denoising attempts to remove the 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 a non redundant and unique representation of the signal. Several properties of the wavelet transform, which make this representation attractive for denoising, are

- •Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- •Sparsity - the majority of the wavelet coefficients are small in magnitude.
- •Edge detection - large wavelet coefficients coincide with image edges.
- •Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters

During a two level of decomposition of an image using a scalar wavelet, the two-dimensional data is replaced with four blocks. These blocks correspond to the sub bands that represent either low pass filtering or high pass filtering in each direction. The procedure for wavelet decomposition consists of consecutive operations on rows and columns of the two-dimensional data. The wavelet transform first performs one step of the transform on all rows. This process yields a matrix where the left side contains down sampled low pass coefficients of each row, and the right side contains the high pass coefficients. Next, one step of decomposition is applied to all columns; this results in four types of coefficients, HH, HL, LH and LL.

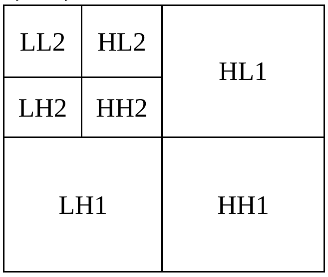

Fig. 1 Two-Level Image decomposition by using DWT

A. *Wavelet Noise Thresholding*

All the wavelet filters use wavelet thresholding operation for denoising [2], [11], [12].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. The basic Procedure for all thresholding method is as follows:

- Calculate the DWT of the image.
- Threshold the wavelet coefficients. (Threshold may be universal or sub band adaptive)
- Compute the IDWT to get the denoised estimate.
- There are two thresholding functions frequently used, i.e. a hard threshold, a soft threshold. The hard-thresholding is described as

$$\eta_1 (w) = wI (| w |> T) \tag{1}$$

Where w is a wavelet coefficient, T is the threshold. The soft-thresholding function is described as

$$\eta_2 (w) = (w - \mathrm{sgn}(w) T) I (| w | > T) \tag{2}$$

Where sgn(x) is the sign function of x. The soft-thresholding rule is chosen over hard-thresholding, .

As for as speckle (multiplicative nature) removal is concerned a preprocessing step consisting of a logarithmic transform is performed to separate the noise from the original image. Then different wavelet shrinkage approaches are employed. The different methods of wavelet threshold denoising differ only in the selection of the threshold.

IV. .PARAMETER COMPUTATION FOR THRESHOLD

In general a small threshold value will leave behind all the noisy coefficients and subsequently the resultant denoised image may still being noisy. On the other hand a large threshold value makes more number of coefficients as zero which directs to smooth the signal destroys details and the resultant image may cause blur and artifacts. So optimum threshold value should be found out, which is adaptive to different sub band characteristics. Thus the innovative aspects of the present work consist of the estimating appropriate threshold by analyzing the statistical parameters of the wavelet coefficients. Our threshold is based on Universal thresholding function.

In the original work of Donoho et. al [12], proposed universal threshold

$$l = s_n \sqrt{\log 2N} \tag{3}$$

has been derived, which depends on the image size (N) and the noise standard deviation σ_n. It is easy to implement 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. Threshold does not depend on the content of the image; rather it depends on the size of image. Based on this we proposed our threshold by estimating a parameter weighted variance (d). Instead of applying a pre-selected uniform threshold, we propose a *background- support threshold selection* scheme for a coefficient-dependent choice of the threshold. We define *weighted variance* for coefficient Y [m, n] for threshold determination. The parameter weighted variance d involves neighboring coefficients of the wavelet decomposition for the estimation of the local variance. It is based on the estimation of the local weighted variance $\sigma_w[m, n]^2$ of each wavelet coefficient Y[m, n] at level l and orientation O using a window N *of size* 5×5 .The weighted variance of a coefficient $Y[m, n]$ with respect to the window of size 5 x 5 with weights $w = \{w_{i,j}, i, j \in N\}$ is defined by

$$d = s_w [m,n]^2 = \frac{\sum_{i,j\in N} w_{i,j} Y[m,n]^2}{\sum_{i,j\in N} w_{i,j}} \tag{4}$$

$$l(m,n) = \frac{s_n^2}{d} \tag{5}$$

V. SELECTION OF PARAMETERS

The parameter noise variance s^2 needs to be estimated first. It may be possible to measure s^2 based on information other than the corrupted image and it is estimated from the sub band HH_1 by the robust median estimator,

$$s^2 = \left[\frac{median\left|_{m,n}\right|}{0.6745}\right]^2 \tag{6}$$

Weighted variance (d) of a given wavelet coefficient is determined by the weight in a local window. The weight w_2 corresponding to the vertical neighbors of the current coefficient is the most dominant one. The current coefficient to be processed is suppressed by choosing the corresponding weight w_0 to be much lower than that of w_2.This helps to distinguish between signal coefficients and noise coefficients. The selection of weights for the calculation of weighted variance would be in such a way that the estimated threshold minimizes the Mean square error. By some means the local weighted variance should reflect the correlation structure of wavelet coefficients .In general, magnitudes of wavelet coefficients show correlations which decay exponentially with the distance. Also, in a 2-D wavelet decomposition, the decay depends strongly on the orientation o of the given band, *i.e.*, along the direction of highpass filtering the correlation typically goes down more rapidly than in lowpass direction. Also, the correlation depends on the level *l* of decomposition, such that on higher levels one observes a much stronger decay than on lower levels. By putting these observations together, we finally arrived at a model of weights. The weight w_2 corresponding to the vertical neighbors of the current coefficient is the most dominant one. followed by the weight w_9 of the corresponding parent coefficient in the next upper level, hence capturing the most significant correlation patterns of both intra- and interband type. The current coefficient to be processed is suppressed by choosing the corresponding weight $w0$ to be much lower than that of the immediate vertical neighbors. This helps to further discriminate between correlated signal coefficients and isolated noise coefficients. Weights $w1 \neq w2 \neq w3 \neq 0$, to distinguish between signal components and coefficients related to noise.

W_8	W_6	W_4	W_6	W_8
W_7	W_3	W_2	W_3	W_7
W_5	W_1	W_0	W_1	W_5
W_7	W_3	W_2	W_3	W_7
W_8	W_6	W_4	W_6	W_8

Fig: 2 5*5 window with variable weight for calculating weighted variance

VI. IMAGE DENOISING PROCEDURE

This section depicts the image-denoising algorithm, which achieves near optimal soft thresholding in the wavelet domain for recovering original signal from the noisy one. The wavelet transform employs Daubechies' least asymmetric compactly supported wavelet with eight vanishing moments with four scales of orthogonal decomposition. It has the following steps.

- Transform the multiplicative noise model into an additive one by taking the logarithm of the original speckled data.
- Log I(x, y) = log S(x, y) + log η(x, y).
- Perform the DWT of the noisy image up to 2 levels (L=2) to obtain seven sub bands, which are named as LL_1, HH1, LH_1, HL_1, HH_2, LH_2, HL_2 and LL_2.
- Obtain noise variance using 6.
- Calculate the weighted variance of signal d by 4.
- Compute the threshold value l for each pixel by 5.
- Threshold all sub band coefficients using Soft thresholding by substituting the threshold value obtained from 5.
- Perform the inverse DWT to reconstruct the denoised image.
- Take Exponent.

VII. EXPERIMENTAL RESULTS & DISCUSSIONS

The performance of the wavelet thresholding method that has been proposed in this paper is investigated with simulations. Denoising is carried out for ultrasound image with Speckle noise of variance σ^2 = *0.03, 0.04, 0.05, 0.06, 0.07* using standard speckle filters, Bayes thresholding, proposed thresholding and Wiener filter, the best linear filtering possible. The version used is the adaptive filter, wiener2, in the MATLAB image processing toolbox. For objective evaluation, the signal to noise ratio (*SNR*) of each denoised image has been calculated using Signal to Noise Ratio (SNR), which is defined as

$$PSNR = 10\log_{10} \frac{255}{MSE} \tag{11}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j)-Y(i,j)\right)^2 \tag{12}$$

Where *X, Y* represent the original and denoised images, respectively.

The performance of the different denoising schemes is compared in Table I and we have presented a comparative study of various wavelet filters and standard speckle filters for **U**ltrasound image in terms of PSNR The performance of Speckle filters such as *Kaun* filter, *Frost* filter, the conventional approach in speckle filtering the homomorphic *Wiener filter* are measured here. We apply Matlab's spatially adaptive Wiener filter. We have done all the simulations in MATLAB tool. All the wavelet-based techniques used Daubechies 4 wavelet basis and 1 level of decomposition. Chart 1 depicts the graphical representation of comparison of different denoising methods for Ultrasound image.

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. From table I wavelet shrinkage filters are performed well than standard adaptive speckle filters. *VisuShrink* is the least effective among the methods compared. It is easy to implement 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. Threshold does not depend on the content of the image; rather it depends on the size of image. Thus, the threshold does not adapt well to discontinuities in the signal. Among these, *BayesShrink* clearly performs the best. Among all our method performs well in terms of both PSNR and visual quality.

Table I
COMPARISON OF PSNR OF DIFFERENT DENOISING FILTERS FOR ULTRASOUND IMAGES CORRUPTED BY SPECKLE NOISE.

σ^2	0.02	0.03	0.04	0.05	0.06	0.07
Frost	22.565	22.045	21.295	20.455	19.615	19.067

Kaun	22.685	22.327	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
proposed	32.614	31.695	31.136	30.771	29.837	27.495

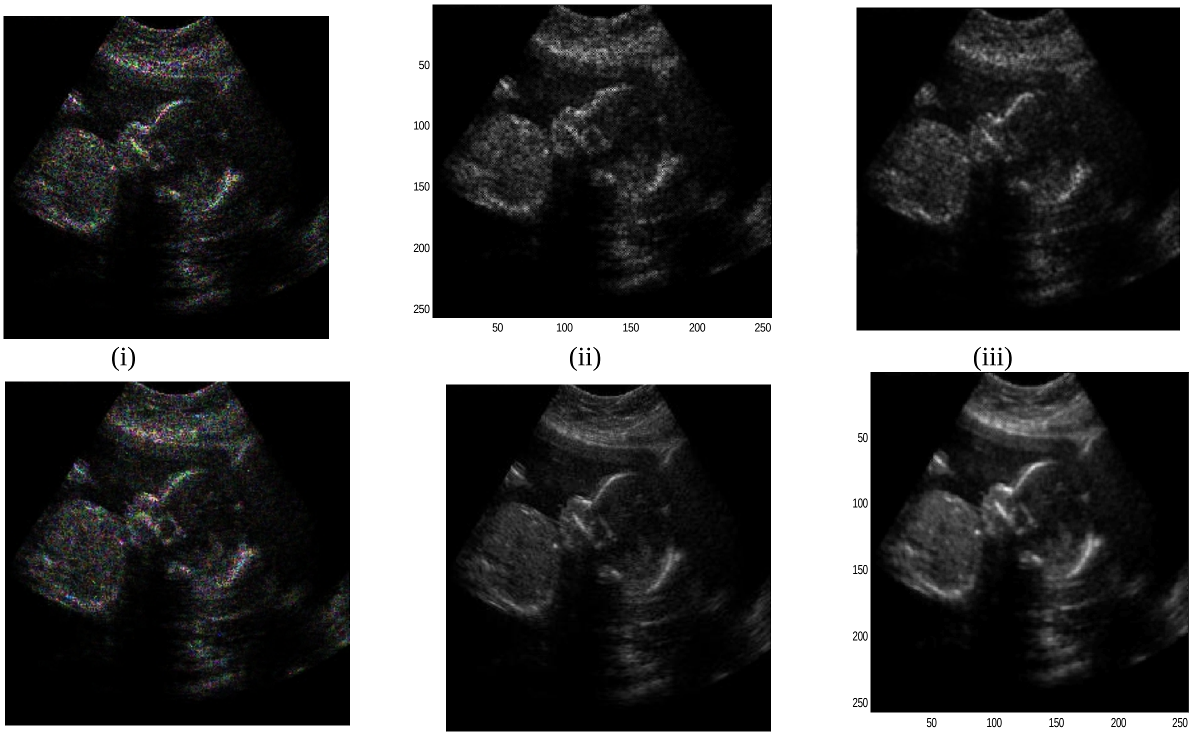

Fig. 3. Denoising of ‘Ultrasound’ image corrupted by Speckle Noise of Variance of 0.07.
(i) Noisy image, (ii) Kaun filter, (iii) Frost filter, (iv) Weiner filter (iv) Bayes threshold (vi) Proposed method

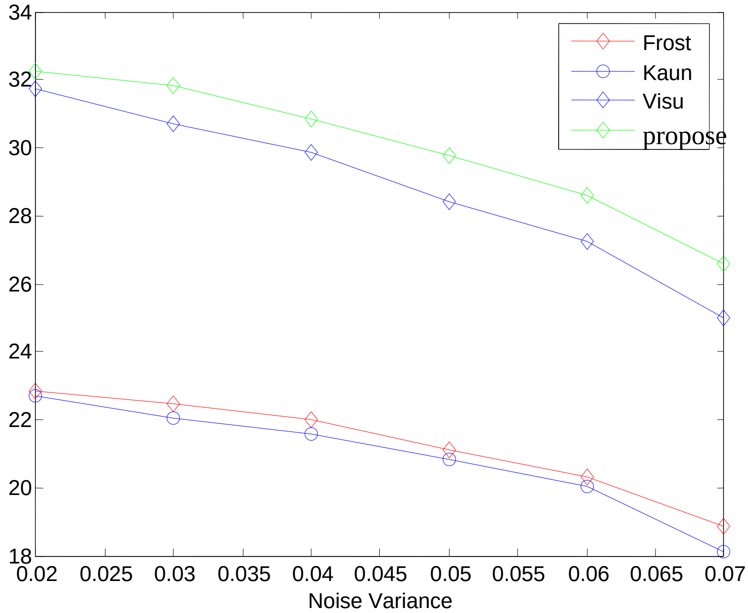

Fig. 4 Comparison Chart of PSNR of different denoising methods for ‘Ultrasound’ Image

I. CONCLUSION

In this work we have introduced a relatively simple context-based model for adaptive threshold selection within a wavelet thresholding framework. Estimations of local weighted variance with appropriately chosen weights are used to adapt the threshold. The proposed thresholding technique outperforms all the standard speckle filters, Weiner filter Visu shrink, and Bayes shrink methods. However, by visual inspection it is evident that the denoised image, while removing a substantial amount of noise, suffers practically no degradation in sharpness and details Experimental results show that our proposed method yields significantly improved visual quality as well as better SNR compared to the other techniques in the denoising literature.

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