Adaptive Noise Reduction in Ultrasonic Images

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***Abstract*—Ultrasonic image is an imaging technique that is commonly used for medical diagnostics. Unfortunately, the quality of ultrasonic images is limited, mainly due to speckle noise. Speckle noise reduction is one of the most important processes in enhancing the quality of ultrasonic images. In this paper, an adaptive noise reduction technique in wavelet domains for ultrasonic images is studied. First, a logarithmic transformation is performed on an original ultrasonic image in order to convert a multiplicative noise to an additive one. Next, Stationary Wavelet Transform is used to decompose the image resulting from the first step into four subbands. Then, an adaptive Wiener filter is applied to all detailed subbands in order to suppress additive noises in these subbands. Subsequently, the reconstructed image is derived by performing an inverse Stationary Wavelet Transform on those resulting subbands and following by an exponential transformation. The performance of the studied algorithm is evaluated objectively and subjectively on several ultrasonic images and it is compared against several well-known methods, such as Median filter, Wiener filter, Discrete Wavelet Transform based on soft thresholding, and Discrete Wavelet Transform along with Wiener filter. The results clearly demonstrate the superior performance of the studied method in terms of signal to mse ratio (S/mse), edge preservation (β) values as well as perceptible image quality.**

Keywords–Stationary Wavelet Transform; Multiplicative Noise Reduction; Wiener Filter; Ultrasonic Images.

I. INTRODUCTION

Ultrasound imaging is predominant and plays an important role in medical diagnosis because it is a noninvasive, nonradioactive, real-time and inexpensive modality [1]. However, ultrasonic images usually suffer from three component kinds of noises. The first arises from the electronics of the detection system. For instance, the signal intensity of the backscattered ultrasound signals is affected by the operating frequency of the transducer: the higher the frequency, the greater the tissue attenuation, which therefore produces a lower signal-to-noise ratio (SNR). The second source, speckle, corresponds to coherent wave interference in tissue. It is well known to be signal-dependent in ultrasound imaging systems. The final term, clutter, is applied to signals arising from side lobes, multipath reverberation, and tissue motion that add noise to the ultrasound images [1].

Over the years, speckle noise suppression has been widely studied and considered. When filtering random noise from an image, there are two main issues to be considered: how much noise has been removed, and how well edges are preserved without blurring. Traditionally, there are several simple techniques for noise suppression, such as a moving average filter and Gaussian filter. Being merely low-pass filters, they can effectively suppress noise, but they fail to preserve many useful details [2]. For speckle noise reduction techniques, some of the well-known filters include Lee filter, Kuan filter, median filter, and homomorphic Wiener filters [3]–[5]. These filters can effectively suppress speckle noise, but they fail to sufficiently preserve the edges. In the past decade, there has been considerable interest in using Wavelet transform as a powerful tool for recovering signal from noisy data. This method is generally referred to as a wavelet shrinkage technique. In 1995, D. L. Donoho presented a soft threshold method for denoising in one dimensional signal [6]. S. Chang, B. Yu and M. Vetterli introduced an adaptive wavelet threshold for image denoising and compression. They proposed a new shrinkage method, BaeyShrink [7], which also outperformed Donoho and Johnstone's Sureshrink [8]. Furthermore, other authors proposed probabilistic methods for speckle noise reduction in the wavelet domain [9]–[12]. Recently, A. K. Gupta and D. Sain have proposed a speckle reduction technique using a logarithmic threshold contourlet [13]. The method proposed by C. Barcelos and L. Vieira used an adaptive edge-controlled variation function to detect and reduce speckle noise [14]. Another proposed approach uses adaptive block-based singular value decomposition for speckle noise suppression [15].

In this paper, an adaptive noise suppression technique for ultrasonic images is proposed. The studied method is a preprocessing step for speckle noise reduction, before applying a feature extraction process [16]. First, a logarithmic transformation is applied to an original image in order to convert the multiplicative noise into additive noise. Next, Stationary Wavelet Transform (SWT) is used to decompose the transformed image resulted from the first step into four subbands. SWT is a wavelet transform algorithm that do not decimated but instead padding the filters with zeros [17]. That is, all the subband images would have the same size as the original images. Therefore, it has several advantages, as compared to Discrete Wavelet Transform (DWT). First, the transformation is translation-invariance. In addition, there is no information loss in each subband, since there is no downsampling process, unlike DWT. Then, an adaptive Wiener filter is applied to all the detailed subbands. An adaptive Wiener filter is a well-known filtering technique that has been applied not only to reduce stationary noise in noisy images but also to suppress blocking artifacts [18]. As a result, a reconstruct images derived from the studied method would be smoother, as compared to other filtering techniques, e.g., a block-based SVD based approach [15]. Finally, an inverse

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SWT is computed and applied to the exponential transformation to reconstruct the denoised image. Then, in order to evaluate the performance of the studied method, the quality of reconstructed images derived from the studied method is compared against other existing approaches, such as median filter, Wiener filter, Discrete Wavelet Transform (DWT), based on soft thresholding, and DWT coupled with Wiener filter.

The rest of this paper is organized as follows. In Section II, a studied method for speckle noise reduction is described in details. Then, the quantitative image quality measurements and experimental results are given in Section III and IV respectively. Finally, the conclusion remarks are provided in Section V.

II. STUDIED METHOD

Similar to homomorphic Wiener filtering, the studied method could be used to reduce a speckle noise in medical images, which is done in the SWT domain. The block diagram of studied method is illustrated in Figure 1. Details are as follows:

- Take a logarithmic transformation to the original image (f), which yields image result (g).
- Perform a 2-D SWT on the log transformed image in order to decompose the transformed image g into four subbands (LL, LH, HL and HH).
- Perform a 2-D adaptive Wiener filter only in the detailed subbands (LH, HL and HH), window size of 7x7 is chosen which yields the image result ($\hat{Y}$).
- Apply the inverse 2-D SWT which yields a denoised image ($\hat{g}$).
- Take the exponential transformation of the denoised image to get the reconstructed image ($\hat{f}$).

The two main components of this method: 2-D stationary wavelet transform and adaptive wiener filter, are described below.

A. 2-D stationary wavelet transform

Unlike the conventional Discrete Wavelet Transformer (DWT), the two dimensional Stationary Wavelet Transformer (2-D SWT) is based on the idea of no decimation, which means the SWT is translation-invariant [19]. It applies the DWT and omits both down-sampling in the forward and up-sampling in the inverse transformation. 2-D SWT can be implemented by first applying the DWT along the rows of an image, and then applying it on the column of an image. Therefore, a transformed image is decomposed into four subbands, which are the same size as the original image. The LL band contains the approximation coefficients, the LH band contains the horizontal details, the HL band contains the vertical details and the HH band contains the diagonal details. Without translation-invariance, slight shifts in the input signal will produce variations in the wavelet coefficients that might introduce artifacts into the noise reduction process. This property is good for noise removal because the noise is usually spread over a small number of neighbouring pixels. The 2-D SWT decomposition scheme is illustrated in Figure 2.

B. Adaptive wiener filter

Two dimensional Wiener filter is a minimum mean-square error filter [20]. It is a nonlinear spatial filtering that moves a window or kernel over each pixel in the image, computes and replaces the central pixel values under the window. It uses a collection of window sizes to estimate the noise power from the local image mean (μ) and standard deviation (σ). The output of 2-D Wiener filter [21] [22] is defined by:

$$\hat{Y}(x_i, y_j) = \mu + \frac{\sigma^2 - v^2}{\sigma^2} \times (Y(x_i, y_j) - \mu) \tag{1}$$

where μ and σ^2 represents the local mean and standard deviation obtained from the noisy image window respectively. Y is the noisy pixel and $\hat{Y}$ is the filtered pixel. Also, v is the noise variance, estimated from the average of all the local estimated variances in the image. Note that, only an odd number should be used as the size of the kernel. If the size is too large, important feature will be lost. On the other hand, if the size is too small, noise reduction may not yield good results. In general, a kernel size of 3x3 and 7x7 provides good results [13].

III. QUANTITATIVE QUALITY MEASURES

To quantify the achieved noise reduction ability performance, there are two main issues to be considered, which are how much noise has been removed, and how well edges are preserved without blurring. In the past decade, there have been many quantitative quality measurements proposed. In this research study, three image quality measurements: Mean Square Error (MSE), Signal to MSE ratio (S/mse), and edge preservation (β) are computed using original and reconstructed image data [23] [24].

A. Mean Square Error (MSE)

$$MSE = \frac{1}{mn} \sum_{i,j=1}^{m,n} (\hat{S}_{i,j} - S_{i,j})^2 \tag{2}$$

Where n and m are image dimension. $\hat{S}$ and S are referred to reconstructed and original images, respectively. The higher MSE value denotes the lower image quality.

B. Signal to MSE ratio(S/mse)

To evaluate speckle noise reduction, a Signal to MSE ratio (S/mse) is used, instead of the standard signal to noise ration. It is defined as below:

$$\frac{S}{MSE} = 10 \log_{10} \frac{\frac{1}{mn} \sum_{i,j=1}^{m,n} (S_{i,j}^2)}{MSE} \tag{3}$$

The lower S/mse means the lower image quality.

C. Edge preservation (β)

To consider the performance of edge preservation, a parameter β based on a correlated operation between original and reconstructed images is used and given by:

$$\beta = \frac{\Gamma(\Delta s - \bar{\Delta s}, \Delta \hat{s} - \bar{\Delta \hat{s}})}{\sqrt{\Gamma(\Delta s - \bar{\Delta s}, \Delta s - \bar{\Delta s}) \Gamma(\Delta \hat{s} - \bar{\Delta \hat{s}}, \Delta \hat{s} - \bar{\Delta \hat{s}})}} \tag{4}$$

where $\bar{\Delta s}$ and $\bar{\Delta \hat{s}}$) are the mean values in the region of interest(ROI) $s_{i,j}$ and $\hat{s}_{i,j}$ respectively. Also, Δs and $\Delta \hat{s}$ represent the high pass filtered operation of s and $\hat{s}$, respectively,

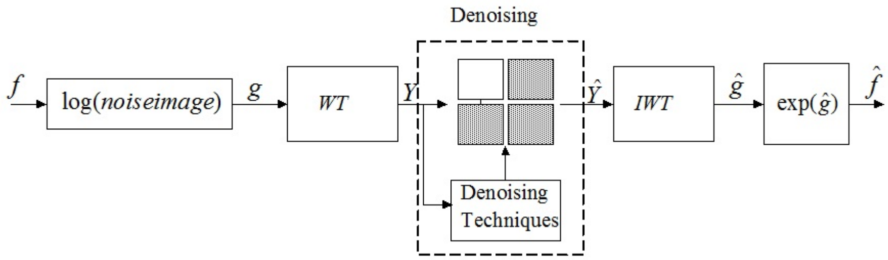


Figure 1. Block diagram for speckle noise reduction in SWT domain [16].

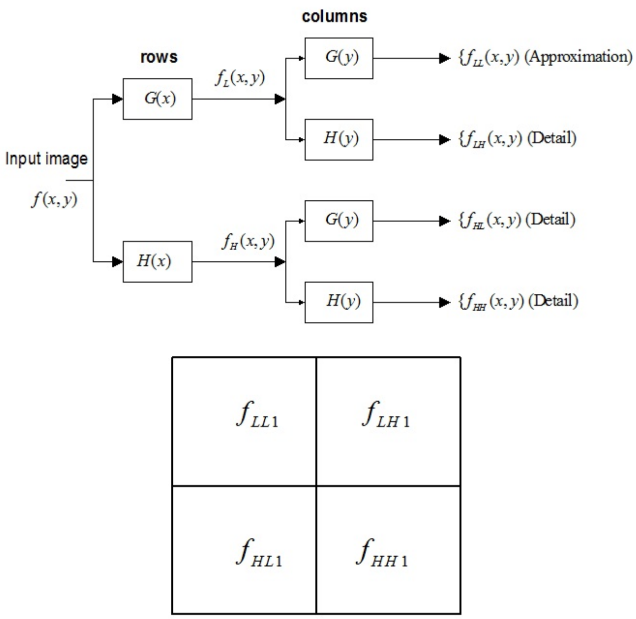


Figure 2. 2-D Stationary Wavelet Transform Decomposition Scheme.

obtained from a 3x3 pixel standard approximation of Laplacian operator where:

$$\Gamma(s_1, s_2) = \sum_{i,j=1}^{m,n} s_{1(i,j)} s_{2(i,j)} \tag{5}$$

Here, the larger value of β means the better feature preservation ability of the reconstructed image.

IV. Experiments

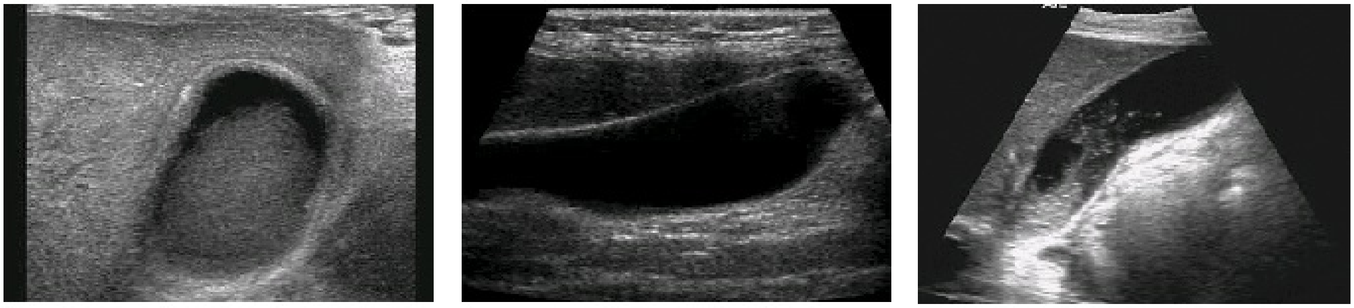
In this part of the experiment, to validate the performance of the studied method, various cholecystitis ultrasonic images are used, as shown in Figure 3. The image size is 256x256. A number of experiments were conducted and compared with other traditional methods, which were 2-D median filter (7x7), 2-D adaptive Wiener filter (7x7), DWT with soft thresholding, and DWT along with Wiener filter. The experiments reported in this section have been tested using MATLAB 10.0 - R2010b (64 bit). All the wavelet-based techniques used Daubechies 4 wavelet basis, with one level of DWT and SWT decomposition. In fact, noise is generally spread over in detailed subbands, due to the components of highpass wavelet filters. Therefore, the 2-D adaptive Wiener filter is applied only in detailed subbands. To quantify the achieved performance in terms of the ability of speckle noise reduction and edge preservation, three original cholecystitis ultrasonic images, as illustrated in Figure 3, are used. These images are first corrupted with noise at variance of 0.08 where the noisy images are depicted in Figure 4(a). Then, different speckle noise reduction techniques are applied on these noisy images. Then, the quality of reconstructed images are evaluated using S/mse and β. The numerical results, presented in Table I, show that the proposed approach outperforms other methods in terms of S/mse and β.

TABLE I. EXPERIMENTAL RESULTS OBTAINED BY VARIOUS NOISE REDUCTION TECHNIQUES AT NOISE VARIANCE OF 0.08.

Images	Methods	Mask	S/MSE	β
Cholecystitis (a)	Median filter	7x7	15.7360	0.1333
	2-D Wiener filter	7x7	16.1618	0.2575
	DWT with soft thresholding	–	16.4526	0.2457
	DWT and Wiener filter	7x7	16.6765	0.2999
	SWT and Wiener filter	7x7	**17.2609**	**0.4224**
Cholecystitis (b)	Median filter	7x7	12.3104	0.1451
	2-D Wiener filter	7x7	12.3741	0.2412
	DWT with soft thresholding	–	113.1566	0.2388
	DWT and Wiener filter	7x7	13.5087	0.2923
	SWT and Wiener filter	7x7	**14.6532**	**0.4480**
Cholecystitis (c)	Median filter	7x7	16.4115	0.1157
	2-D Wiener filter	7x7	16.8007	0.3557
	DWT with soft thresholding	–	17.0805	0.2670
	DWT and Wiener filter	7x7	17.3977	0.3237
	SWT and Wiener filter	7x7	**17.8405**	**0.4297**

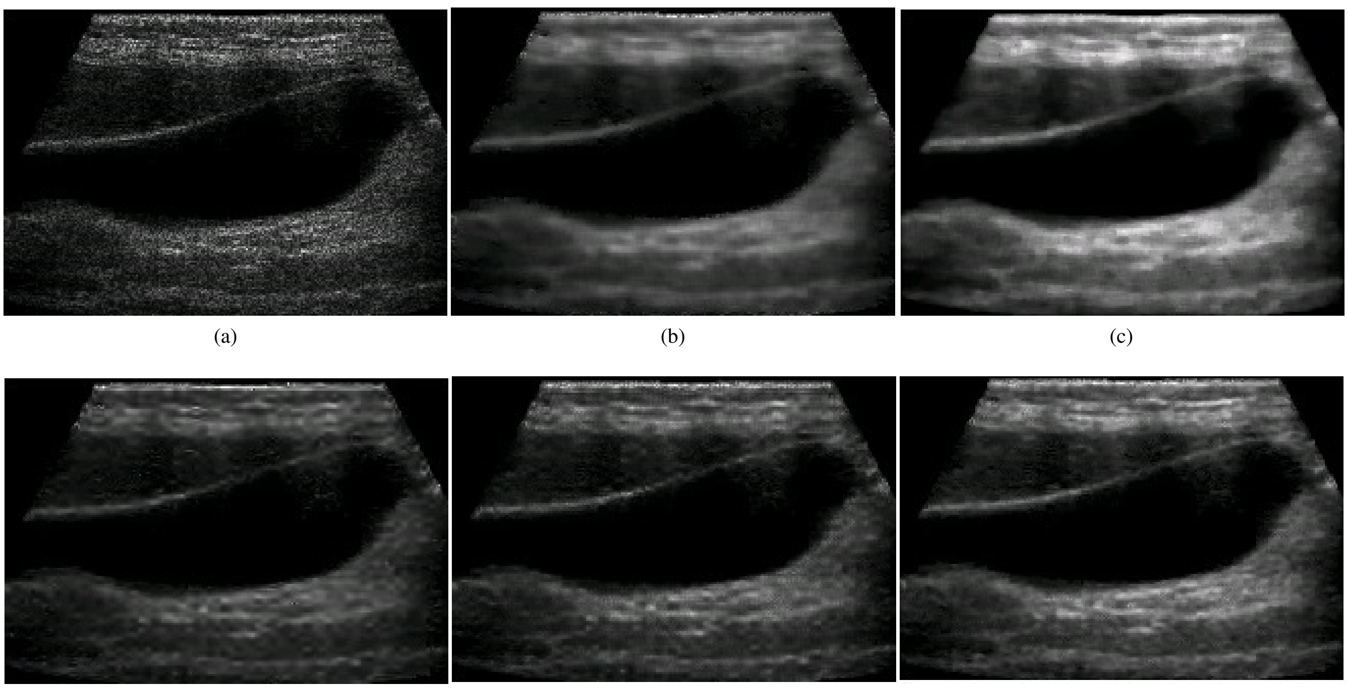
To visually compare with all other methods, the comparatives of various results are shown in Figure 4. As for the results, Figure 4(b) and Figure 4(c) are operated by a fixed window size 7x7 in spatial domain. The reconstructed images are overly smoothed and have artifacts around the object. On the other hand, the combination of Wiener filter and SWT outperforms DWT with soft thresholding and DWT along with Wiener filter, as shown in Figure 4(d), 4(e) and 4(f). It is seen that the studied method can efficiently reduce noise in the homogeneous area and simultaneously preserve the edges feature thereby resulting in a better reconstructed image in terms of visual perception.

Next, in order to evaluate performance of studied method more extensively, the realistic noisy liver and kidney ultrasonic



(a) (b) (c)

Figure 3. Cholecystitis ultrasound images.



(a) (b) (c)

(d) (e) (f)

Figure 4. Results of various speckle reduction methods: (a) noisy cholecystitis ultrasound image, (b) denoised image using 2-D median filter, (c) denoised image using 2-D Wiener filter, (d) denoised image using DWT with soft thresholding, (e) denoised image using DWT and Wiener filter, and (f) denoised image using SWT and Wiener filter.

images are also used. The original images and resulting images of different speckle noise reduction techniques are shown in Figure 5 and Figure 6 respectively. The results demonstrate that SWT along with Wiener filter outperforms other methods since it can effectively reduce speckle noises and simultaneously preserve edge features as well as important details of the ultrasonic images.

V. Conclusion and future work

In this research, the main aim is to study and compare the different methods of speckle noise suppression in ultrasonic images. The studied method uses SWT to transform a logarithmic image and then applies an adaptive Wiener filter in each detailed subband. The advantage of multi-resolution analysis using SWT for speckle noise reduction is that it can reduce noise while preserving the feature structure of the reconstructed image. From the preliminary results, the combination of the SWT and adaptive Wiener filter has better quantitative and qualitative performances, compared with existing methods. Future work, the use of different types of mother wavelets and other types of wavelet transform, such as Wavelet Packet Transform, will be investigated in order to get the best result. Moreover, subjective assessment has to be performed by ultrasonographers in order to visually ensure the reconstructed image quality. Consequently, the best technique could be developed and be implemented in hardware.

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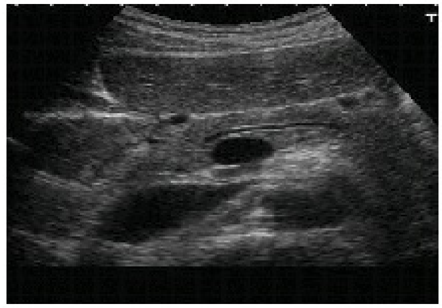
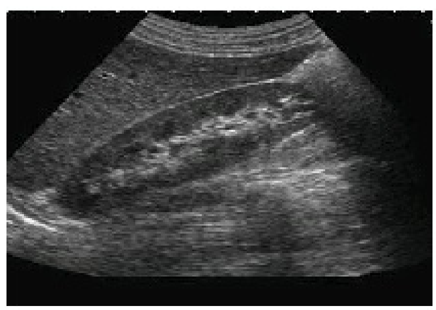


(a)

(b) (c) (d)

Figure 5. Results of various speckle reduction methods: (a) noisy liver ultrasound image, (b) denoised image using DWT with soft thresholding, (c) denoised image using DWT and Wiener filter, and (d) denoised image using SWT and Wiener filter.



(a)

(b) (c) (d)

Figure 6. Results of various speckle reduction methods: (a) noisy kidney ultrasound image, (b) denoised image using DWT with soft thresholding, (c) denoised image using DWT and Wiener filter, and (d) denoised image using SWT and Wiener filter.

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