Ultrasound Image Denoising using Multiscale Ridgelet Transform with Hard and NeighCoeff Thresholding

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Abstract - Ultrasound imaging utilizes sound waves reflected from different organs of the body to give local details and important diagnostic information on the human body. However, using ultrasound images for diagnosis is difficult because of the existence of speckle noise in the image. The speckle noise is due to interference between coherent waves which are backscattered by targeted surfaces and arrive out of phase at the sensor. This hampers the perception and the extraction of fine details from the image. Speckle reduction/filtering i.e. visual enhancement techniques are used for enhancing the visual quality of the images. The multscale ridgelet transform based denoising algorithm for Ultrasound images is proposed for effective edge preservation in comparison to filtering techniques using the Adaptive Filters.

Keywords - *Image Denoising; Multiscale Ridgelet Transform; Ultrasound Images.*

I. INTRODUCTION

A. Motivation

Digital images play an important role in daily life application such as television, ultrasound imaging, magnetic resonance imaging, computer tomography as well as in areas of research and technology. Ultrasound imaging has become a popular imaging modality as it is noninvasive, portable, safe, relatively inexpensive, and provides a real-time image formation. The imaging process in ultrasound imaging is based on the principle of reflection of sound waves. The tissue is insonified with sound pulses with a fixed frequency. Subsequently, the reflections that are generated during wave propagation in the tissue due to difference in tissue densities. These reflections are registered as a function of time. The time elapsed between the emission of a pulse and the reception of its echoes reveals the depth of the reflecting objects or tissues interfaces. The intensity of the echo waves yields information on the acoustics properties of the object. These received signals are used to construct an image [1]. However, a fundamental problem of ultrasound images is the poor quality, mainly caused by multiplicative speckle noise. Speckle is mainly caused by interference between coherent waves which are backscattered by targeted surfaces and arrives out of phase at the sensor. Speckle can be modeled as random noise (irregular pattern), which degrades the detection of low contrast lesions and also reduces the ability of a human observer to resolve fine detail. So the quality of the image can be improved by using speckle reduction (filtering) techniques. Hence, speckle suppression by means of digital image processing should improve image quality and possibly the diagnostic potential of medical ultrasound.

Many speckle reduction/filtering or visual enhancement techniques like mean and median filtering [2] are used for enhancing the visual quality of the image. Various techniques of speckle reduction and enhancement have been developed. The most widely cited and applied filters in this category include the Lee Filter [3], the Frost Filter [4], and the SRAD Filter [5]. The Lee Filter forms an output image by computing the linear combination of the center pixel intensity in the filter window with the average intensity of the window. So, the filter achieves a balance between straightforward averaging (in homogeneous regions) and the identity filter (where edges and point features exist). This balance depends on the coefficient of variation inside the moving window. The Frost Filter also strikes a balance between Averaging and the All-Pass Filter. In this case, the balance is achieved by forming an exponentially shaped filter kernel that can vary from a basic average filter to an identity filter on a point wise, adaptive basis. Again, the response of the filter varies locally with the coefficient of variation. In case of a low coefficient of variation, the filter is more average-like, and in cases of a high coefficient of variation, the filter attempts to preserve sharp features by not averaging.

Jean-Luc Starck et al. [6] have proposed the radon, ridgelet and curvelet transforms for image denoising. They apply these digital transforms to the denoising of some standard images embedded in white noise. S.Sudha. et al. [7] in their paper, "Wavelet Based Image Denoising using Adaptive Thresholding", describes a

new method for suppression of noise in image by fusing the wavelet Denoising technique with optimized thresholding function, improving the denoised results significantly. T. Ratha et al [8] describes and analyses an algorithm for cleaning speckle noise in ultrasound medical images. This algorithm is based on Morphological Image Cleaning algorithm (MIC).

Although the existing despeckle filters are termed as "edge preserving" and "feature preserving", there exist major limitations in their filtering approach. Firstly, the filters are sensitive to the size and shape of the filter window. Using a filter window that is too large compared to the object of interest causes over-smoothing and blurring of the edges. A small window decreases the smoothing capability of the filter and leaves speckle. In terms of window shape, a square window (as is typically applied) will lead to corner rounding of rectangular features that are not oriented at perfect 90 rotations. Secondly, the existing filters do not enhance edges but only inhibit smoothing near edges. When any portion of the filter window contains an edge, the coefficient of variation is high and smoothing is inhibited. Therefore, noise or speckle in the neighborhood of an edge will remain after filtering. Thirdly, the despeckle filters are not directional. In the vicinity of an edge instead of inhibiting smoothing in directions perpendicular to the edge and encouraging smoothing in directions parallel to the edge, all smoothing is precluded.

B. Main Contribution

1. To overcome the limitations of SRAD Filter and wavelet transform, the multiscale ridgelet filter [9] is proposed for denoising of ultrasound images with improved thresholds for preserving and enhance the edges. The performance of each filter will be compared using parameter PSNR (Peak Signal to Noise Ratio).

2. The organization of the paper as follows: In section I, a brief review of image denoising and related work is given. Section II, presents a concise review of ridgelet transform. Section III, presents the thresholding methods for image denoising and proposed system framework. Experimental results and discussions are given in section IV. Based on above work conclusions are derived in section V.

II. RIDGELET TRANSFORM (RT)

A. Radon Transform

The Radon transform of an object f is the collection of line integrals indexed by $(\theta, t) \in [0, 2\pi) \times R$ given by

$$Rf(\theta, t) = \int f(x_1, x_2)\delta(x_1 \cos\theta + x_2 \sin\theta - t)\, dx_1 dx_2 \qquad (1)$$

where δ is the Dirac distribution. The ridgelet coefficients $CRT_f(a, b, \theta)$ of an object f are given by analysis of the Radon transform via

$$CRT_f(a, b, \theta) = \int Rf(\theta, t)a^{-1/2}\psi((t-b)/a)\, dt \qquad (2)$$

Basic algorithm for discrete radon transform is as follows

1. Compute the two-dimensional Fast Fourier Transform (FFT) of function f.

2. Using an interpolation scheme, substitute the sampled values of the Fourier transform obtained on the square lattice with sampled values of $\hat{f}$ on a polar lattice: that is, on a lattice where the points fall on lines through the origin.

Compute the one-dimensional Inverse Fast Fourier Transform (IFFT) on each line; i.e., for each value of the angular parameter.

B. Discrete Ridgelet Transform (DRT)

A continuous ridgelet transform is calculated by applying 1D wavelet transform to the slices of radon transform $R_f(\theta, .)$. In radon transform a famous projection-slice theorem is used

$$\hat{f}(\omega \cos\theta, \omega \sin\theta) = \int R_f(\theta, t)e^{-2\pi i\omega x}\, dt \qquad (3)$$

This theorem says that the Radon transform can be obtained by applying the one-dimensional inverse Fourier transform to the two-dimensional Fourier transform of function restricted to radial lines through the origin. The relation among the Fourier, radon and ridgetet domain is depicted in Fig. 1.

To complete the ridgelet transform, apply a one-dimensional wavelet transform along the radial variable in Radon space. The sum up of above procedure is shown in Fig. 2 in the form of flow chart. The DRT of an image of size $n \times n$ is an image of size $2n \times 2n$, introducing a redundancy factor equal to 4 [6].

C. Multiscale Ridgelet Transform (MRT)

Multiscale ridgelets based on the ridgelet transform combined with a spatial bandpass filtering operation to isolate different scales as shown in [6].

Algorithm:

1. Apply the `a trous algorithm with J scales [10].

2. Apply the radon transform on detail sub-bands of J scales.

3. Calculate ridgelet coefficients by applying 1-D wavelet transform on radon coefficients.

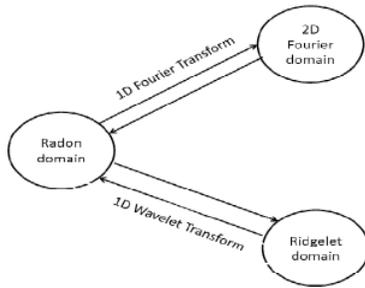Get the multiscale riglet coefficients for *J* scales.
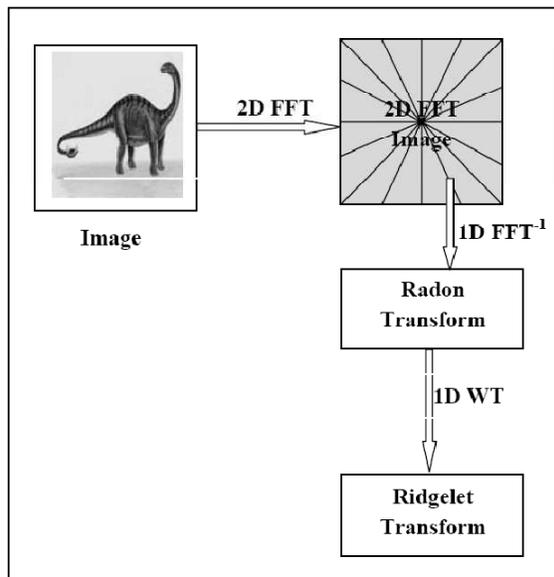

Fig. 1: Relations between transforms.

Fig. 2: Flowchart of Discrete ridgelet transform.

III. IMAGE DENOISING

A. Denoising by Hard Thresholding

Suppose that one is given noisy data of the form:

$$\overline{I}(x, y) = I(x, y) + \sigma Z(x, y) \qquad (4)$$

Where $Z(x,y)$ is unit-variance and zero-mean Gaussian noise. Denoising a way to recover $I(x,y)$ from the noisy image $\overline{I}(x, y)$ as proper as possible. Rayudu et al. [11] have proposed the hard thresholds for Ultrasound image denoising as shown below:

Let y_λ be the noisy ridgelet coefficients (y = MRT*I). They used the following hard-thresholding rule for estimating the unknown ridgelet coefficients:

$$\begin{aligned}\hat{y}_\lambda &= y_\lambda; \qquad if \ |y_\lambda|/\sigma \ge k\,\tilde{\sigma}_\lambda \\ \hat{y}_\lambda &= 0 \ ; \qquad else\end{aligned} \qquad (5)$$

In their experiments, they have chosen a scale dependent value for k; k = 4 for the first scale (j = 1) while k = 3 for the others (j > 1).

Algorithm:

1. Apply multiscale ridgelet transform to the noisy image and get the scaling coefficients and multiscale ridgelet coefficients.

2. Chose the threshold by Eq. (5) and apply thresholding to the multiscale ridgelet coefficients (leave the scaling coefficients alone).

3. Reconstruct the scaling coefficients and the multiscale ridgelet coefficients thresholded and get the denoised image.

B. NeighCoeff Thresholding algorithm

The hard thresholding is ineffective in many examples. Though the NeighCoeff [12] scheme which considers neighboring multiscale ridgelet coefficients to be proposed in this work. In this scheme, the size of neighbor varies with the dependence of the coefficients.

$$S_{j,k}^2 = \sum_{n=-N}^{N} MRT_{j,k+n}^2; \quad N = N_0 - j \qquad (6)$$

Here j is the level in curvelet decomposition and (2N+1) is the size of neighbor. N_0 can be selected according to the size of image and the support of the multiscale ridgelet coefficents:

$$MRT_{j,k} = \begin{cases} MRT_{j,k}\left(1 - \dfrac{\alpha\lambda^2}{S_{j,k}^2}\right) & if \ S_{j,k}^2 \ge \alpha\lambda^2 \\ 0 & else \end{cases} \qquad (7)$$

where λ is given by *2logn* and α is a parameter that adjusts the threshold.

C. Proposed Denoising Algorithm

Algorithm:

1. Apply multiscale ridgelet transform to the noisy image and get the scaling coefficients and multiscale ridgelet coefficients.

2. Chose the threshold by Eq. (6) and (7) and apply thresholding to the multiscale ridgelet coefficients (leave the scaling coefficients alone).

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IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Removal of noises from the images is a critical issue in the field of digital image processing. The phrase Peak Signal to Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupted noise that affects the fidelity of its representation. As many signals have wide dynamic. The MSE and PSNR is defined as:

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \qquad (8)$$

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - k(i,j)\|^2 \qquad (9)$$

Fig. 3 shows the denoising results of different methods on five sample images. In Fig. 3, the first column presents the five sample ultrasound images; second column shows the sample images with Gaussian noise of zero mean and 0.01 variance; third, fourth and fifth columns denote the denoising results of the SRAD, wavelet and proposed method (multiscale ridgelet transform) respectively. From Fig. 3, it is clear that the proposed method outperforming the SRAD and wavelet based denoising techniques.

Figure 2. TABLE I DENOISING RESULTS OF VARIOUS METHODS IN TERMS OF PSNR UNDER GAUSSIAN NOISE OF ZERO MEAN AND 0.01 VARIANCE.

Image No.	SRAD	Wavelets	Multiscale Ridgelet
1	27.79	27.5	34.81
2	26.28	24.88	33.52
3	23.99	18.57	23.76
4	27.49	33.73	41.19
5	20.48	15.42	17.9

Figure 3. TABLE II DENOISING RESULTS OF VARIOUS METHODS IN TERMS OF PSNR UNDER GAUSSIAN NOISE OF ZERO MEAN AND 0.02 VARIANCE.

Image No.	SRAD	Wavelets	Multiscale Ridgelet
1	22.24	26.89	32.4
2	20.13	23.64	29.81
3	18.8	17.69	21.6
4	23.19	32.64	37.21
5	15.66	14.64	16.49

Table I & II show the results of different methods on five sample images. From Table I & II, it is clear that the proposed method outperforming the SRAD and wavelet based denoising techniques.

V. CONCLUSIONS

Negotiation between the preservation of useful diagnostic information and noise suppression must be treasured in medical images. 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. Removing noise from the original image or signal is still a challenging problem for researchers. The multscale ridgelet transform based denoising algorithm for Ultrasound images is proposed for effective edge preservation in comparison to filtering techniques using the Adaptive Filters.

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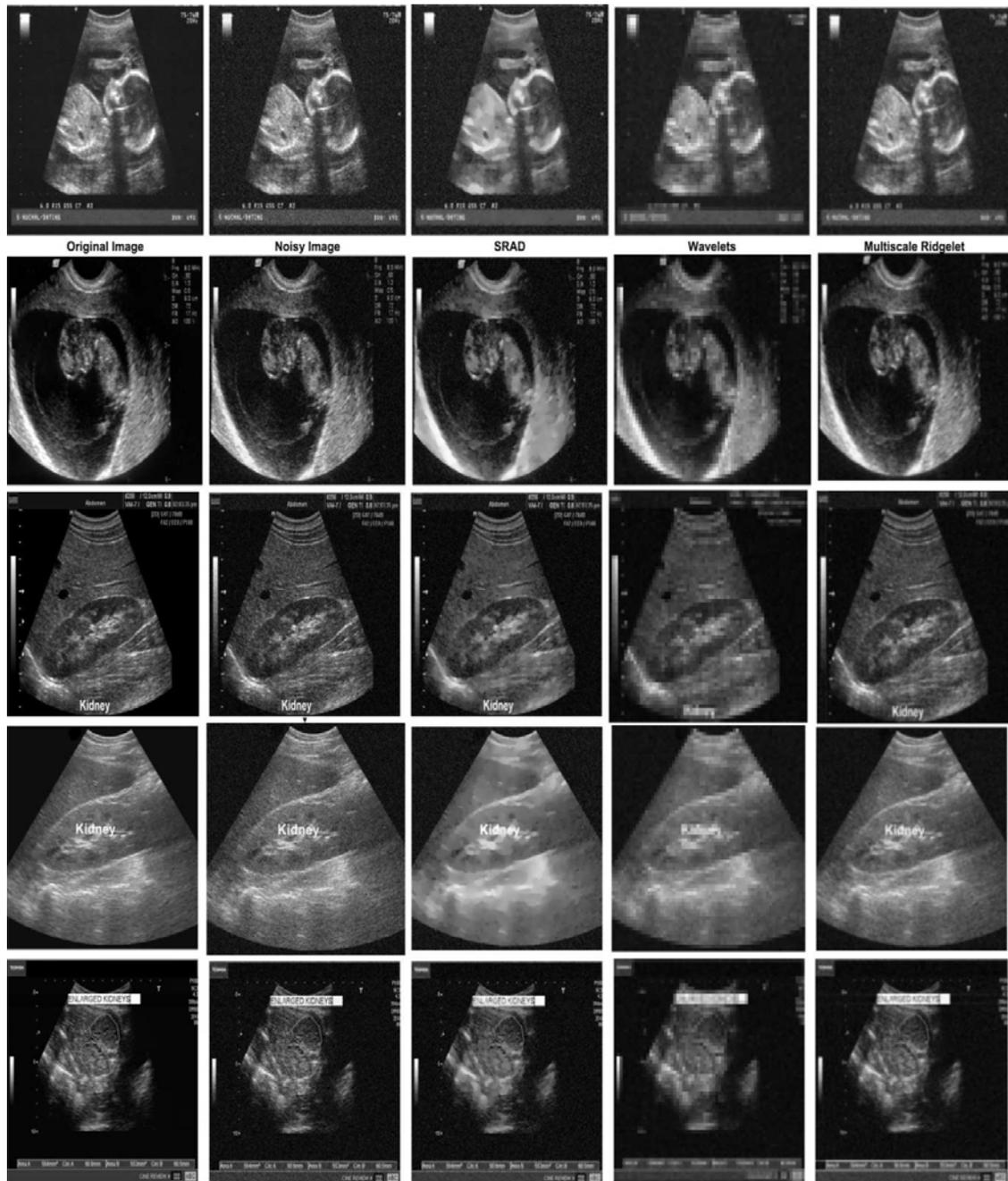
Fig. 3: (first column) sample images, (second column) noisy images, (third column) denoising results of SRAD technique, (fourth column) denoising results of wavelet transform technique, and (fifth column) denoising results of the proposed method