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Wavelet-Based Ultrasound Image Denoising: Performance Analysis and Comparison

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***Abstract*— Ultrasound images are generally affected by multiplicative speckle noise, which is mainly due to the coherent nature of the scattering phenomenon. Speckle noise filtering is thus a critical pre-processing step in medical ultrasound imaging provided that the diagnostic features of interest are not lost. A comparative study of the performance of alternative wavelet based ultrasound image denoising methods is presented in this article. In particular, the contourlet and curvelet techniques with dual tree complex and real and double density wavelet transform denoising methods were applied to real ultrasound images and results were quantitatively compared. The results show that curvelet-based method performs superior as compared to other methods and can effectively reduce most of the speckle noise content of a given image.**

I. Introduction

SPECKLE phenomena affect all coherent imaging systems including systems using laser, SAR and medical ultrasound imaging techniques. Therefore it is important to reduce the speckle effect in the medical images often used for diagnostic applications.

Several methods have been proposed in the past for speckle removing from ultrasound images. The classical Wiener filter is shown not to be adequate for this purpose since it is basically designed for additive noise suppression [1]. Because of the multiplicative nature of speckle noise, Jain [2] developed a homomorphic filter where the multiplicative noise is converted into additive noise using the logarithm of the image. Wiener filter could then partially remove the resulting additive noise. Others have used adaptive weighted median filtering approach, introduced in [3] which can effectively suppress the speckle noise but it fails to preserve many useful details since it is merely a low-pass filter.

Traditional spatial and filtering-based methods for denoising often reduce noise at the cost of blurred features while single-scale conventional methods for contrast enhancement may amplify noise [4]. Recently, there has been a considerable interest in using wavelet transform as a powerful tool for recovering signals from noisy data. Regularized soft thresholding (wavelet shrinkage) is adopted to reduce noise energy within finer scales using nonlinear processing of feature energy for contrast enhancement [5].

Non-linear estimators have also been developed based on formal Bayesian theory, that outperform the classical linear processors and simple thresholding estimators in removing noise from regular scene images. A generalized Laplacian model for the subband statistics of the signal has also been developed and has been used for noise-removal [6].

In this article a comparative analysis of the performances of various wavelet based methods for ultrasound image denoising is presented. We will consider dual tree wavelet transform in its three different structures namely complex, real, double density as well as contourlet and curvelet transform. The paper is organized as follows. Section II describes the methods used in the comparative study. Section III introduces the image data set employed in this work. The results are illustrated in section IV. Finally, section V concludes the paper.

II. Methods

The speckle noise in an ultrasound image is generated by the fact that there are a number of elementary scatterers within each resolution cell of the image that reflect the incident wave back towards the ultrasound sensor. The backscattered coherent waves with different phases undergo constructive and destructive interferences in a random manner. The resulting image is thus corrupted by a random granular pattern, called speckle noise which hinders the interpretation of the image content [6].

Various methods have been proposed in the past to reduce the effect of the speckle noise within ultrasound images [7]. Wavelet transform based methods for noise reduction for application in different categories of images have gained considerable attention during past decade. This is mostly due to effective noise reduction capability of these methods while preserving the main image/signal characteristics regardless of the image frequency content [7].

A tradeoff between noise reduction and the preservation of the actual image features has to be made in order to enhance the relevant image content for diagnostic purposes. Even though wavelets have been extensively used for denoising speckle noise of ultrasound images, it has been

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shown [6] that speckle denoising using contourlets, provides superior results as compared with those of the wavelet shrinkage and dual tree wavelet transform methods in terms of the signal to noise ratio. In the following characteristics of these different techniques and their application for speckle denoising will be addressed.

Due to the multiplicative nature of the speckle noise as with most of the previously reported research works [8] the logarithm of the input image is calculated first.

A. Dual tree Wavelet Transform

To overcome oscillations of the wavelet coefficients at the points of singularity and lack of directional selectivity in higher dimensions as well as aliasing and consequent shift variance problems, complex wavelet transform (CWT) employs analytic filters having real and imaginary parts that are constructed from Hilbert transform (HT) pair and thus securing magnitude-phase representation and shift invariance with no aliasing. Complex wavelet transform as a moderately redundant multi-resolution transform with decimated subbands runs in two DWT trees (real and imaginary) of real filters that produce real and imaginary parts of the coefficients.

B. Dual tree Complex wavelet transform

Complex wavelets have not been widely used in image processing due to the difficulty in designing complex filters which satisfy a perfect reconstruction property. An effective approach for implementing analytic wavelet transform was first introduced by Kingsbury in 1998 which is called the dual-tree CWT (Complex Wavelet Transform) [4]. This technique uses two trees of real filters to generate real and imaginary parts of the wavelet coefficients separately.

The dual tree CWT employs two real DWTs; the first DWT yields the real part of the transform while the second DWT gives the imaginary part. The two real wavelet transforms use two different sets of filters, with each satisfying the perfect reconstruction (PR) conditions. The two sets of filters are jointly designed so that the overall transform is approximately analytic. The filters are themselves real; no complex arithmetic is required for the implementation of the dual-tree CWT. We also note that the dual-tree CWT is not a critically sampled transform; it is two times expansive in 1-D because the total output data rate is exactly twice the input data rate. This introduces redundancy in transform which is considered a point of merit for dual tree CWT in noise reduction applications. The inverse of the dual-tree CWT is as simple as the forward transform. To invert the transform, the real part and the imaginary part are each inverted—the inverse of each of the two real DWTs are used to obtain two real signals. These two real signals are then averaged to obtain the final output. Note that the original signal x(n) can be recovered from either of the real part or the imaginary part alone; For denoising applications, instead of shrinking each wavelet coefficient directly, one can shrink the magnitude of the complex wavelet to improve the de-noising performance.

C. Contourlet

The contourlet transform is a 2-D transform technique recently developed for image representation and analysis [9]. It was originally defined in the discrete domain, but in [9] authors proved its convergence in the continuous domain. It was constructed in a discrete-domain for multi resolution and multi direction expansion using non-separable filter banks. This construction resulted in a flexible multiresolution, local, and directional image expansion using contour segments, and thus it is named contourlet transform. The discrete contourlet transform has a fast iterated filter bank implementation algorithm that requires an N order operation for N pixel images.

The improvement in approximation by contourlets based on keeping the most significant coefficients, will directly lead to improvement in numerous applications including compression, denoising and feature extraction. In image denoising, random noise will generate significant wavelet coefficients similar to true edges, but is less likely to generate significant contourlet coefficients. Consequently, thresholding for denoising in contourlet is more efficient than thresholding in wavelet transform.

D. Ridgelet

We describe ridglet in this part since it is utilized as a first stage of curvelet transform in each of the scales in transform domain. Ridgelets have found several applications in image processing. They can be adapted to represent objects with curved edges using an appropriate multiscale localization where at a sufficiently fine scale; curved edges can be approximated by a straight line. A standard ridgelet transform can be applied to a given image where 2D FFT of the image is computed first followed by replacing the sampled values of Fourier transform that are derived on the square lattice, by the corresponding sampled values on a polar lattice. The 1D inverse FFT on each angular line is then computed where this is followed by application of 1D scale wavelet transform on the resulting angular lines in order to obtain the ridgelet coefficients [10].

E. Curvelet

Curvelets proposed by E. Candes and D. Donoho [11, 12], constitute a relatively new family of frames that are designed to represent edges and other singularities along curves much more efficiently than the traditional wavelet based transforms. The idea of curvelets is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law width ≈ length2. This can be done by first decomposing the image into suitable subbands, i.e. separating the object into a series of disjoint scales. Then, each scale is analyzed by means of a local ridgelet transform. Curvelets are used in object detection in speckle images [13].

III. MATERIALS

A. Images

We use two sets of images gathered from ultrasound image gallery [14] and Philips [15] datasets. Since the size of speckle noise in these data is not known, in order to compare the results of denoising by different methods, we use these data as reference data assuming they are clean and without speckle noise.

B. Noisy Images

In order to generate speckle noisy image, we apply the multiplicative speckle noise on the ultrasound image according to (1) in which S is the noise-free ultrasound image and η is uniformly distributed random noise with mean 0 and variance υ.

$$I = S * \eta \tag{1}$$

The input image to the denoising methods is the logarithm of the noisy image in which the speckle is transformed from multiplicative noise into an additive noise according to (2):

$$\log I(m,n) = logS(m,n) + \log\eta\,(m,n) \tag{2}$$

IV. RESULTS

For application of dual tree denoising method, it is necessary that an optimum threshold level be obtained. This is achieved by calculating the mean squared error (MSE) evaluated from the noisy and de-noised images for different threshold values and selecting a threshold which yields minimum MSE. Several optimum threshold values under different transform methods are shown in table I.

TABLE I
OPTIMUM THRESHOLD FOR DUAL TREE DENOISING

Optimum Threshold	Method
0.02	Dual tree Double Density WT
0.015	Dual tree Complex WT
0.015	Dual tree Real WT

We have used peak signal to noise ratio (PSNR) and the mean square of the differences between noisy and clean images (RMS) to compare the different denoisng results. The PSNR and RMS measures are used in approximately all the papers which are about the denoising of the ultrasound images. They are defined as follow:

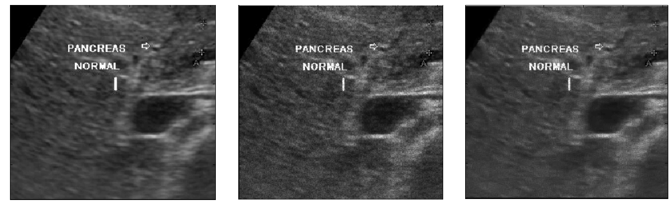
$$\mathrm{MSE} = \frac{1}{\mathrm{mn}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \sum_{\mathrm{j}=1}^{\mathrm{n}} [\mathrm{I}(\mathrm{i},\mathrm{j}) - \mathrm{K}(\mathrm{i},\mathrm{j})]^2 \tag{3}$$

And

$$\mathrm{PSNR} = 10\log\left(\frac{\mathrm{MAX}_{\mathrm{I}}^2}{\mathrm{MSE}}\right) \tag{4}$$

Here, $\mathrm{MAX_I}$ is the maximum possible pixel value of the noisy image (I(i,j)) and K(i,j) is the denoised image. As it is shown in table II the complex dual tree wavelet transform yields better denoising results as compared with real dual tree wavelet transform and double density dual tree wavelet transform. The complex dual tree result has greater PSNR and lower RMS values. The denoising methods are applied on noisy images with the same amount of speckle noise, so the results are comparable.

The original noise-free image and its noisy version and the denoised image by dual tree complex method are shown in Fig. 1.



(a) Original image (b) Noisy image (c) Denoised image

Fig. 1. Dual tree complex wavelet transform denoising result $\upsilon = 0.03$

The details of the ultrasound image in Fig. 1 along with the white written note can be used for visual assessment of the denoising approach. The denoised images of contourlet and curvelet denoising methods are shown in Fig. 2 and Fig. 3.

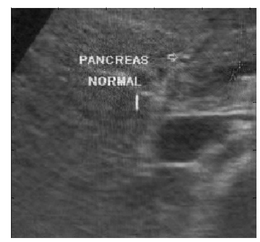
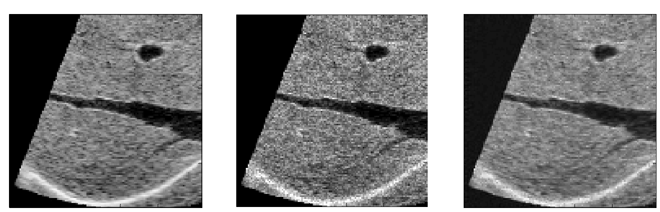


Fig. 2. Contourlet denoising result $\upsilon = 0.03$

As it can be seen, the speckle noise is not fully removed using contourlet based denoising and the speckle on the black part of the background image remains to be denoised.

Fig. 3. Curvelet denoising result $\upsilon = 0.03$



(a) Original image (b) Noisy image (c) Denoised image

Fig. 4. Curvelet denoising result $\upsilon = 0.03$

Fig. 3 and Fig. 4 show the denoising results of curvelet method on two different images from two different dataset.

The blurring effect of other despeckling method is rarely seen in the results of curvelet method.

TABLE II
DENOISING RESLUTS

Method / Result	Noisy Image	Dual Tree Real	Dual Tree Complex	Dual Tree Double Density	Curvelet	Contourlet
PSNR	27.451	30.5628	31.101	30.013	32.426	29.483
RMS	0.029	0.021	0.019	0.022	0.018	0.026

In table II the PSNR and RMS values of different denoisng methods are shown for comparison of the results. The curvelet method for noise variance $\upsilon = 0.03$ yields better result than the other method. It is shown that the result of dual tree complex wavelet is very close to those of curvelet but still a lower PSNR value.

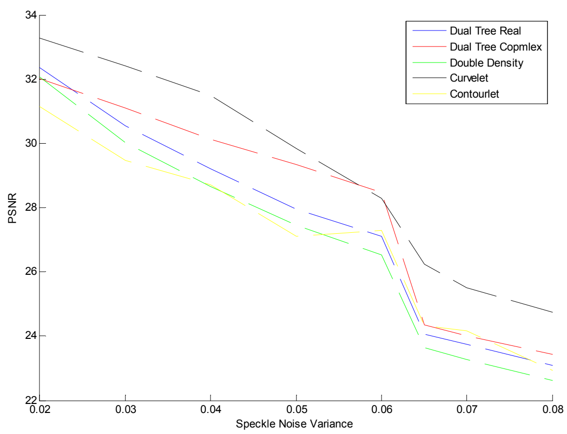


Fig. 5. Comparing the denoising results of different methods

Fig.5 shows the results of denosing under different methods considered in this paper as a function of noise variance. It can be concluded that different optimum denosing method are to be applied for different range of variances, however curvelet yields superior results as compared with other methods. The PSNR of the curvelet denoising results is significantly higher than those of other methods.

When the noise variance is around $\upsilon = 0.06$, the dual tree complex method results are near curvelet results and a bit better. All in all curvelet denoising method is appropriate for all levels of speckle noise.

Besides the MSE and PSNR measures, visual quality of the denoised image is usually used for evaluating the denoising results. Among all these methods, curvelet performs well in terms of both PSNR and visual quality.

Visual quality was assesses by a physician and showed improved results. This expert confirmed the better visualization of the details in denoised images in comparison with noisy images.

V. CONCLUSION

Dual tree wavelet transform for the reason of the redundancy of the transform, it yields enhanced denoising results as compared with standard wavelet shrinkage denoising methods. Among dual tree methods, complex dual tree wavelet exhibit a superior performance for denoising that is attributed to the redundancy of the transform as well as large number of the coefficients that is generated in transform domain.

Curvelet denoising method is more efficient in denoising speckled ultrasound images due to the ability of curvelet to recover signals in different directions as compared with other methods including dual tree complex wavelet transform. The method yields better results as compared with contourlet which is attributed to the frame structure used for representing edges and singularities along curves.

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