Speckle Reducing Contourlet Transform for Medical Ultrasound Images

P.S. Hiremath, Prema T. Akkasaligar, and Sharan Badiger

Abstract—Speckle noise affects all coherent imaging systems including medical ultrasound. In medical images, noise suppression is a particularly delicate and difficult task. A tradeoff between noise reduction and the preservation of actual image features has to be made in a way that enhances the diagnostically relevant image content. Even though wavelets have been extensively used for denoising speckle images, we have found that denoising using contourlets gives much better performance in terms of SNR, PSNR, MSE, variance and correlation coefficient. The objective of the paper is to determine the number of levels of Laplacian pyramidal decomposition, the number of directional decompositions to perform on each pyramidal level and thresholding schemes which yields optimal despeckling of medical ultrasound images, in particular. The proposed method consists of the log transformed original ultrasound image being subjected to contourlet transform, to obtain contourlet coefficients. The transformed image is denoised by applying thresholding techniques on individual band pass sub bands using a Bayes shrinkage rule. We quantify the achieved performance improvement.

Keywords—Contourlet transform, Despeckling, Pyramidal directional filter bank, Thresholding.

I. Introduction

IMAGE denoising is a procedure in digital image processing aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality. Image denoising still remains the challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Medical ultrasonography is one of the popular techniques for imaging diagnosis and is preferred over other medical imaging modalities because it is noninvasive, portable and does not provide any harmful radiations [1]. The disadvantage of ultrasonography is the poor quality of images, which is due to the presence of multiplicative speckle noise.

In the recent years, there have been many challenges to reduce the speckle noise using wavelet transform as a multiresolution image processing tool. In [2-3], a survey of different digital image processing techniques used in enhancing the quality and information content in ultrasound image is presented. Hiremath et al.[4] have proposed despeckling medical ultrasound images using wavelet transform and Bayes thresholding. The wavelet transform is well adapted to point singularities, so it has a problem with orientation selectivity. This is a major drawback for wavelet-based image denoising technique. The contourlet transform has been recently developed by Do and Vetterli [5] to overcome the limitations of wavelets. It is based on an efficient two-dimensional multiscale and directional filter bank that can deal effectively with images having smooth contours. S.Sateesh [6] have discussed the removal of Gaussian noise from MR images.

The new algorithm based on the contourlet transform is found to be more efficient than wavelet methods. G.Balaji [7] have presented an algorithm based on contourlet transform for despeckling the satellite images. Mao-Yu Huang et al. [8] have presented a contourlet based speckle reduction method for breast ultrasound images. The double iterated filter bank structure and a small redundancy at most 4/3 using two thresholding methods shows a great promise for speckle reduction. Hiremath et al. [9] have proposed despeckling medical ultrasound images using contourlet transform using Bayes shrinkage rule. In this paper, we propose to apply the contourlet transform to medical ultrasound image despeckling and compare the performance of the proposed method with wavelet based method of despeckling. The algorithm is also tested on ovarian ultrasound images to show improvements in segmentation. The ovarian ultrasound imaging is an effective tool in infertility treatment. The edge based segmentation method with Gaussian low pass filter for noise removal has been employed by Hiremath and Tegnoor [10] for follicle detection. Due to speckle noise, finding the object boundaries is difficult and thus leads to poor segmentation. A new improved algorithm is proposed by Hiremath and Tegnoor [11] in which follicle segmentation is achieved by using a speckle reduction method based on contourlet transform for denoising medical ultrasound images [9] in preprocessing phase and edge based method for segmentation phase. The experimental results of a method in [11] are compared with the manual results by medical expert and with method described in [10]. The proposed method in [11] yields better segmented regions as compared to the method in [10], which does not produce optimal segmentation results for the sample images considered in the experimentation [11]. Further, the contourlet transform based method yields better classification rate (75.2%) due to improved segmentation as compared to the Gaussian low pass filter based method (classification rate is 62.3%)[12].

II. Speckle Noise Model

Images formed with coherent energy, such as ultrasound, suffer from speckle noise. Speckle is a form of locally correlated multiplicative noise that corrupts medical ultrasound

P.S.Hiremath is with the Dept. of P.G. Studies and Research in Computer Science, Gulbarga University, Gulbarga-585106, Karnataka, India,(e- mail: hiremathps53@yahoo.com).

Prema T. Akkasaligar is with Dept. of Computer Science and Engineering, B.L.D.E.As Dr P.G.H. Engineering College, Bijapur-586103, Karnataka, India,(e-mail: premasb@rediffmail.com).

Sharan Badiger is with Department of Medicine, Sri.B.M.Patil Medical College, BLDE University, Bijapur-586103, Karnataka, India, (e-mail: sharanrb@rediffmail.com).

images and makes visual observation difficult. Such noise is generally more difficult to remove than additive noise, because the intensity of the noise varies with the image intensity. The presence of speckle noise in ultrasound images has been documented since the early 1970s, where the researchers Burckhardt [13], Wagner et al [14] and Goodman [15] described the fundamentals and the statistical properties of speckle noise. Speckle occurs especially in images of the liver and kidney whose underlying structures are too small to be resolved by wavelength of ultrasound. Work by Bamber and Daft [16] suggests that speckle may reduce the detectability of a lesion by approximately a factor of eight.

In medical literature, speckle noise is referred to as texture and may possibly contain useful diagnostic information. The desired degree of speckle smoothing preferably depends on the specialists knowledge and on the application. In automatic segmentation, maintaining the sharpness of the boundaries between different image regions is significant while removing the speckle. For visual interpretation, smoothing the texture may be less desirable. Physicians generally have a preference for the original noisy image more willingly, than the smoothed version and 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 preserve the features that are of interest to the physician. The contourlet transform has been recently employed in the field of image denoising, and it has firmly established presence as a dominant denoising tool.

To be able to derive an efficient despeckle filter. a speckle noise model is needed. The speckle noise model for ultrasound images may be approximated as multiplicative [16]. The signal at the output of the ultrasound imaging system may be defined as

$$g(i, j) = f(i, j)u(i, j) + n(i, j) \tag{1}$$

where $g(i, j)$ represents the noisy pixel in the image. $f(i, j)$ represents the noise free pixel,$u(i, j)$ and $n(i, j)$ represent the multiplicative and additive noise, respectively, and i, j are the indices of the spatial locations that belong to the 2D space of real numbers, $i, j \in R^2$.

Wagner et al. [14] showed that the histogram of amplitudes within the resolution cells of the envelope-detected RF signal back scattered from a uniform area with a sufficiently high scatterer density has a Rayleigh distribution with mean proportional to the standard deviation $\alpha, (with\alpha/\mu = 1.91)$. This implies that speckle could be modelled as multiplicative noise. The speckle noise becomes very close to the white Gaussian noise corresponding to the uncompressed Rayleigh signal [17]. In particular, it should be noted that speckle is no longer multiplicative in the sense that, on homogenous regions, $g(i, j)$ can be assumed to be constant, the mean is propositional to variance rather than standard deviation.

In the Eq.1, the effect of the additive noise is considerably smaller compared with that of the multiplicative noise and, hence, it may be written as

$$g(i, j) = f(i, j) + u(i, j). \tag{2}$$

The logarithmic operation transforms the model in the Eq.2 into the classical signal in the additive noise form as

$$log(g(i, j)) = log(f(i, j)) + log(u(i, j)). \tag{3}$$

Thus the problem of despeckling is reduced to the problem of rejecting an additive noise, and a variety of noise suppression techniques could be evoked in order to perform the task.

III. The proposed Contourlet based despeckling algorithm

The noise commonly manifests itself as fine grained structure in an image, which leads to discontinuities at edge points. The contourlet transform exploits smoothness of contour effectively by considering variety of directions following the contours. The transform includes pyramidal directional filter bank [18], in which the Laplacian pyramid [19] is first used to capture the point of discontinuities, then a directional filter bank [20] is used to link point of discontinuities into linear structures. Further, thresholding is performed so as to reduce speckle. The contourlet transform can be designed to be a tight frame along with thresholding in order to achieve denoising of the image more effectively. The steps involved in the proposed method are given in the Algorithm 1.

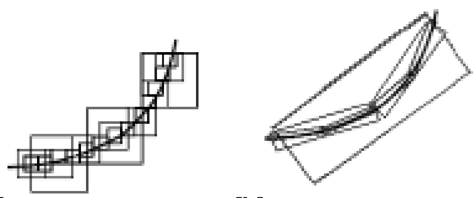
Algorithm 1:Despeckling of an ultrasound image.
Input: Medical ultrasound image.
Output: Despeckled image.
Start
Step 1: Input medical ultrasound image X.
Step 2: Apply log transformation to the input image X.
Step 3: Apply the contourlet transform on the log transformed image of Step 2 upto n levels of Laplacian pyramidal decomposition and m direct ional decompositions at each level.
Step 4: Perform thresholding of contourlet transformed image of Step 3.
Step 5:By performing the inverse contourlet transform on the thresholded image of Step 4, the despeckled image Y is obtained (output image).
Step 6: Compute the performance parameters, namely, variance, MSE, SNR, PSNR, correlation coefficient for the despeckled image Y of Step 5.
Stop

In the Step 3, the contourlet transform can be done upto n levels of Laplacian pyramidal decomposition and m directional decompositions at each level, where n and m depend on the image size. In the Step 4, the contourlet transformed image can be thresholded by selecting either Hard thresholding (HT), Soft thresholding (ST) or Semi-soft thresholding (SST) with Bayes shrinkage rule.

IV. Contourlet Transform

Multiscale and time-frequency localization of an image is offered by wavelets. But, wavelets are not effective in representing the images with smooth contours in different directions. Contourlet Transform (CT) addresses this problem by providing two additional properties viz., directionality and anisotropy [18].

As we find in the Fig. 1, wavelet transforms have square supports that suitably represent point discontinuities. The new-scheme called contourlet transform, representing multi-scaled geometric analysis, contains supports that are elongated and that have multiple directions along the contour. Comparing wavelet transforms, the multi-scaled geometric analysis contains multi-sets of orientational basis functions, which can efficiently present a smoothly curved contour with fewer coefficients.



[a] [b]

Fig. 1. Contourlet and wavelet representation of a contour. (a) Wavelets have square supports that capture the point discontinuities. (b) Contourlets have enlongated supports that capture linear segments of contours.

The contourlet transform can be divided into two main steps: Laplacian pyramid (LP) decomposition and directional filter banks (DFB). Contourlet transform is a multi scale and directional image representation that uses first a wavelet like structure for edge detection, and then a local directional transform for contour segment detection. A double filter bank structure of the contourlet is shown in Fig. 2 for obtaining sparse expansions for typical images having smooth contours. In the double filter bank structure, Laplacian Pyramid (LP) [19] is used to capture the point discontinuities and then followed by a Directional Filter Bank (DFB), which is used to link these point discontinuities into linear structures. The band pass images (d_j[n]) from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image (c_j[n]). The combined result is a double iterated filter bank structure, named pyramidal directional filter bank (PDFB) , which decomposes images into directional subbands at multiple scales.

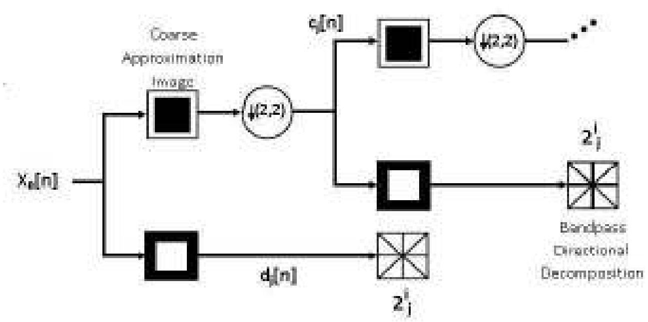
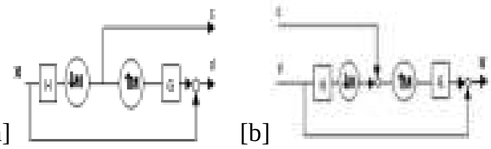


Fig. 2. The flow diagram of the contourlet transform.

A. PDFB: Multiscale decomposition

One way of achieving a multiscale decomposition is to use a Laplacian pyramid (LP) as introduced by Burt and Adelson [21]. The LP decomposition at each step generates a coarse signal c as sampled low pass version of the original image and the difference signal d as a difference between the original and the prediction, resulting in a band pass image (Fig.3 (a)). The process can be iterated on the coarse version. In the reconstruction process, the signal is obtained by simply adding back the difference to the prediction from coarse signal (Fig.3 (b)).



[a] [b]

Fig. 3. Laplacian pyramid scheme (a) Decomposition : The LP generates a coarse approximation image c and a bandpass subband image d as difference between the original signal and the prediction. (b) The reconstruction scheme.

The drawback of the LP is the implicit over sampling. However, in contrast to the critically sampled wavelet scheme, the LP has the distinguishing feature that each pyramid level generates only one band pass image (even for multidimensional cases) which does not have scrambled frequencies. This frequency scrambling happens in the wavelet filter bank when a high pass channel, after down sampling, is folded back into low frequency band, and thus its spectrum is reflected. In the LP, this effect is avoided by down sampling the low pass channel only. LP with orthogonal filters provides a tight frame with frame bounds equal to 1.

B. PDFB: Directional decomposition

To develop efficient or sparse expansions for images having smooth contours, the parabolic scaling relation for curves: $width \alpha length^2$ is used. The contourlet expansion satisfies the parabolic scaling, by using directional decompositions, where the number of directions is doubled at every other finer scale. DFB is designed to capture the high frequency content like smooth contours and directional edges. The DFB is implemented by using a k-level binary tree decomposition that leads to 2^k directional sub bands with wedge shaped frequency partitioning as shown in Fig. 4. But, the DFB used in this work is a simplified DFB [18], which is constructed from two building blocks. The first is a two-channel quincunx filter bank with fan filters. It divides a 2-D spectrum into two directions, horizontal and vertical. The second is a shearing operator, which amounts to the reordering of image pixels. Due to these two operations, directional information is preserved. This is the desirable characteristic in image denoising to improve edge detection efficiency.

V. ADAPTIVE THRESHOLDING

The thresholding approach is sensitive to noise components. In this approach, after contourlet transform, small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing the smallest, noisy coefficients by zero and a backwards contourlet transform on the result may lead to a

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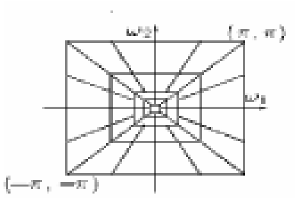

Fig. 4. Pyramidal directional decomposition. s the scale is refined from coarse to fine, the number of directions is doubled at every other subband.

reconstruction with the essential signal characteristics and with less noise. It is important to know about the three categories of thresholding. They are hard thresholding, soft thresholding and semi-soft thresholding. In hard thresholding all coefficients whose magnitude is greater than the selected threshold value λ remains same and the others whose magnitude is smaller than λ are set to zero. It creates a region around zero where the coefficients are considered negligible. In soft thresholding , the coefficients whose magnitude is greater than the selected threshold value are shrunk towards zero by an amount of threshold λ and others set to zero . The aim of semi-soft thresholding is to offer a compromise between hard and soft thresholding by changing the gradient of the slope. This scheme requires two thresholds, a lower threshold λ and an upper threshold λ_1 where λ_1 is estimated to be twice the value of lower threshold λ. The criterion of each scheme is described as follows. Given that λ denotes the threshold limit,X_w denotes the input contourlet coefficients and Y_t denotes the output contourlet coefficients after thresholding, we define the following thresholding functions:

Hard thresholding

$$\mathrm{Y}_t = \left\{ \begin{array}{ll} X_w & if \mid X_w \mid \geq 0 \\ 0 & if \mid X_w \mid < 0 \end{array} \right\} \tag{4}$$

Soft thresholding

$$\mathrm{Y}_t = \left\{ \begin{array}{ll} sign\left\{X_w\right\}(\mid X_w \mid - \lambda) & if \mid X_w \mid \geq \lambda \\ 0 & if \mid X_w \mid < \lambda \end{array} \right\} \tag{5}$$

Semi-soft thresholding

$$\mathrm{Y}_t = \left\{ \begin{array}{ll} 0 & if \mid X_w \mid \leq \lambda \\ sign\left\{X_w\right\} \frac{\lambda_1(\mid X_w \mid - \lambda)}{\lambda_1 - \lambda} & if \lambda < \mid X_w \mid \leq \lambda_1 \\ X_w & if \mid X_w \mid > \lambda_1 \end{array} \right\} \tag{6}$$

A. Shrinkage rule

Bayes shrink has been proposed by Chang, Yu and Vetterli [22]. The goal of this method is to minimize the Bayesian risk, and hence its name Bayes shrink. It is a subband dependent method where threshold level is selected at each subband of resolution in the contourlet decomposition. The Bayes threshold on a given subband s, with zero mean variable X, is given by

$$\lambda_s = \frac{\sigma_n^2}{\sigma_X}, \tag{7}$$

where , the estimated noise variance found as the median of the absolute deviation of the contourlet coefficients on the finest level L_1, is given by

$$\sigma_n = \frac{median(\{\mid X_{i,j} \mid \in L_1\})}{0.67452}, \tag{8}$$

σ_x, the estimated signal variance on the sub band considered, is given by

$$\sigma_x = \sqrt{Max(\sigma_y^2 - \sigma_n^2, 0)} \tag{9}$$

and σ_y^2, an estimate of the variance of the observations, is given by

$$\sigma_y^2 = \frac{1}{N_s} \sum_{k=1}^{N_s} W_k^2, \tag{10}$$

in which, N_s is the number of the contourlet coefficients W_k on the subband considered. In the Eq. 8, the value 0.67452 is the median absolute deviation of normal distribution with zero mean and unit variance. In case of $\sigma_n^2 \geq \sigma_y^2$,$\sigma_x$is zero, and in practice, $\lambda_s(\sigma_x) = max(\{\mid X_{i,j} \mid \in L_1\})$ and all coefficients are set to zero.

VI. FILTER ASSESSMENT

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert. But the Human Visual System (HVS) is so complicated and this cannot give the exact quality of image. The following metrics are used for objective evaluation of the original image X and the despeckled image Y.

Noise variance : It determines the contents of the speckle in the image. A lower variance gives a cleaner image as more speckles are reduced. The formula for calculating the variance is

$$\sigma = \frac{1}{N} \sum_{j=0}^{N-1} X_j^2. \tag{11}$$

Mean Square Error (MSE) : The MSE measures the quality change between the original image (X) and denoised image (Y) and is given by

$$MSE = \frac{1}{N} \sum_{j=0}^{N-1} (Y_j - X_j)^2 . \tag{12}$$

The MSE has been widely used to quantify image quality and when used alone, it does not correlate strongly enough with perceptual quality. It should be used, therefore, together with other quality metrics and visual perception.

Signal-to-Noise Ratio (SNR) : The SNR compares the level of desired signal to the level of background noise. The higher the ratio, the less obtrusive the background noise is. It is expressed in decibels (dB) as

$$SNR = 10log_{10}\left(\frac{\sigma_g^2}{\sigma_e^2}\right) \tag{13}$$

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where, σ_g^2 is the variance of the original image and is the variance of error (Difference between the original and denoised image). Brighter regions have a stronger signal due to more light, resulting in higher overall SNR.

Peak Signal-to-Noise Ratio (PSNR) : The PSNR is computed as

$$PSNR = 10log_{10}\left(\frac{S^2}{MSE}\right) \tag{14}$$

where, S is the maximum intensity in the original image. The PSNR is higher for a better-transformed image and lower for a poorly transformed image. It measures image fidelity, that is, how closely the transformed image resembles the original image.

Correlation Coefficient (CC) : It represents the strength and direction of a linear relationship between two variates. The best known is the Pearson product moment correlation coefficient, which is obtained by dividing the covariance of the two variables by the product of their standard deviation, as given by

$$CC = \frac{N\sum X_iY_i - \sum X_i \sum Y_i}{\sqrt{N\sum X_i^2 - (\sum X_i)^2}\sqrt{N\sum Y_i^2 - (Y_i)^2}} \tag{15}$$

If the correlation coefficient is near to +1, then there exists stronger positive correlation between the original and despeckled image.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

The experimentation is carried out on 52 ultrasound images of size 512 X 512 of kidney using contourlet transform based despeckling method. These images are acquired using the instrument GE LOGIQ 3 Expert system with 5-MHz transducer frequency, in JPEG format. This method is implemented on the Core2Duo system with 1GB RAM and 2.53GHz using MATLAB 7.9. The contourlet transform is performed using double filter bank structure. The six levels of Laplacian pyramidal decompositions are performed using biorthogonal filters with sufficient accuracy numbers such as the 9-7. The directional decompositions up to nine is performed in all the pyramidal levels, using two dimensional ladder filters. The contourlet transform uses the 9/7 filters in LP stage because, in the multiscale decomposition stage, it significantly reduces all inter-scale, inter-location and inter direction mutual information of contourlet coefficients. Similarly, in directional decomposition stage, the ladder structure PKVA filters are more effective in localizing edge direction as these filters reduce the inter-direction mutual information. Further, thresholding schemes such as hard thresholding, soft thresholding or semi-soft thresholding is performed to reduce speckle. The threshold value is calculated using Bayes shrinkage rule. The PSNR is calculated up to 6 LP decompositions. The PSNR value increases up to 2 decompositions using HT, ST and SST, and thereafter reduces. Hence, the optimal level of LP decomposition is 2. The average results obtained for 52 ultrasound images for different reconstruction methods are tabulated. The results obtained for the optimal decomposition of LP levels and directional decompositions using contourlet method based on hard thresholding, soft thresholding and semi-soft thresholding using Bayes rule are given in Tables I, II and III, respectively. The optimal reconstruction method is determined by the criteria, namely, lower Variance and MSE, higher SNR and PSNR values, correlation coefficient is nearly equal to one. From the Tables I, II and III, it is observed that the 2-level Laplacian pyramidal decomposition and 6 directional bandpass sub-bands (2 at level 1, 4 at level 2) using hard thresholding yield better results than soft thresholding and semi-soft thresholding techniques. The frequency bands obtained by using optimal level L2-21 of contourlet decomposition are as follows: the 2nd level has 1 approximation band of size 64 x 64 and 6 detail components (4 of 64 x 64, 2 of 128 x 256). The reconstructed image is the despeckled image. The hard thresholding is better than other thresholding methods, because small coefficients are removed while others are left untouched in HT while in ST or SST, coefficients above the threshold are shrunk by absolute value of threshold.

TABLE I
OPTIMAL DECOMPOSITION OF LP LEVELS AND DIRECTIONAL DECOMPOSITIONS USING CONTOURLET METHOD BASED ON HARD THRESHOLDING (HT) USING BAYES RULE.

Levels	PSNR	Variance	MSE	CC	SNR
L1-2	32.492	0.00881	0.00064	0.9993	26.7434
L2-21	32.770	0.0081	0.00060	0.9995	27.1771
L3-521	26.704	0.00882	0.00303	0.9977	25.1258
L4-4311	25.391	0.00872	0.00463	0.9973	24.8531
L5-51311	25.325	0.00882	0.00470	0.9977	23.8230
L6-121311	25.312	0.00982	0.00470	0.9977	21.8108

TABLE II
OPTIMAL DECOMPOSITION OF LP LEVELS AND DIRECTIONAL DECOMPOSITIONS USING CONTOURLET METHOD BASED ON SOFT THRESHOLDING (ST) USING BAYES RULE.

Levels	PSNR	Variance	MSE	CC	SNR
L1-1	28.394	0.00962	0.00154	0.99910	21.845
L2-21	29.153	0.00923	0.00134	0.99853	24.474
L3-332	20.284	0.00934	0.01332	0.99358	20.862
L4-5331	22.837	0.00905	0.00863	0.99288	19.115
L5-22332	21.620	0.00947	0.01077	0.99292	18.058
L6-123332	22.041	0.00947	0.01033	0.99271	19.420

TABLE III
OPTIMAL DECOMPOSITION OF LP LEVELS AND DIRECTIONAL DECOMPOSITIONS USING CONTOURLET METHOD BASED ON SEMI-SOFT THRESHOLDING(SST) USING BAYES RULE.

Levels	PSNR	Variance	MSE	CC	SNR
L1-1	30.468	0.00963	0.00155	0.99911	22.962
L2-21	30.718	0.00923	0.00134	0.99854	25.269
L3-332	24.575	0.00935	0.01332	0.99358	23.074
L4-5331	24.558	0.00905	0.00864	0.99288	22.997
L5-22332	24.189	0.00947	0.01077	0.99292	20.987
L6-123332	24.200	0.00948	0.01034	0.99272	21.694

The filter assessment parameters MSE, SNR, PSNR, variance and CC are computed for CT using HT,ST and SST. The Figs. 5-7, shows the comparison of the CT and WT methods. From the Figs.5-7, it is observed that, the contourlet based despeckling method shows better performance than the other despeckling methods.

Further, it is found that the despeckling using contourlet transform gives better results than the speckle reduction method based on wavelet transform in particular. The wavelet based Bayes shrink thresholding method is based on separable 2D wavelet transform that has limited directions (Horizontal, Vertical and Diagonal). Speckle noise in medical ultrasound images will generate significant coefficients in wavelet domain just like true detail features, such as edges. The despeckling method in contourlet domain can combine the coefficients along the smooth curve, like the cyst edges and kidney stone contour. However, the speckle noise is less likely to generate significant coefficients using the contourlet method, and thus, it directly leads to better performance in suppressing noise than the Bayes shrink thresholding scheme based on wavelet domain. Another way to analyze the effects of filters is to study the despeckled images and their histograms. In the Fig.9, the various images of the sample medical ultrasound image are represented to compare the results of different despeckling techniques. In the Fig. 9 (b) and (c), the speckle is reduced well, but the structures are blurred and some visible artifacts are introduced. Meanwhile, in Fig. 9 (e) the speckle is reduced well and structures are enhanced. But some details are lost and some are over enhanced. In the result form proposed despeckling method in Fig. 9 (d), the speckle is efficiently reduced and structures are enhanced with almost no loss or noticeable artifact. In Fig. 8, it is observed that the histograms of despeckled image output by proposed method (Fig. 8 (c)) has more similarity to the histogram of original image than that WT method. In other words, the main structure of the histogram does not change after CT transform. The proposed method has more efficiency than wavelet transform method. The medical experts performed the visual inspection to confirm the improvement of the image quality attained by the CT algorithm in our experiment.

VIII. CONCLUSION

In this paper, we have proposed a speckle reduction method based on the contourlet transform for denoising medical ultrasound images. The experimentation is carried out on ultrasound images of kidney. The performance evaluation of the proposed method is done in terms of variance, MSE, SNR, PSNR, Correlation Coefficient are computed from despeckled image. The proposed despeckling method based on contourlet transform performs better than wavelet transform based despeckling method. It is found that, the 2-level of Laplacian pyramidal decomposition and 6 directional bandpass sub-bands (4 of 64 x 64, 2 of 128 x 256) using the hard thresholding with Bayes shrinkage rule yields optimal results for speckle reduction. 2D wavelets work well in isolating the discontinuities at edge points. However, wavelets cannot deal with the geometrical smoothness along contours. The contourlet transform is much more effective in removing speckle noise and preserving wave-fronts than the wavelet transform even for a simple thresholding scheme. The proposed method produces better quality ultrasound images for subsequent computer-assisted image analysis by medical experts.

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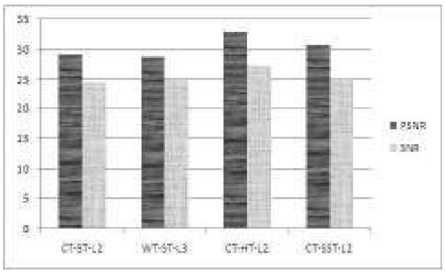

Fig. 5. Statistical feature PSNR, SNR for contourlet transform (CT) and wavelet transform (WT).

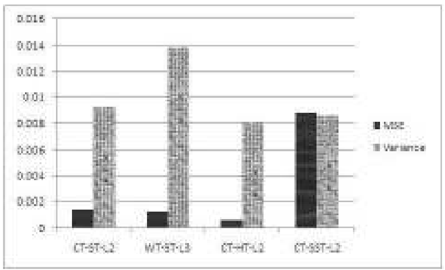

Fig. 6. Statistical feature MSE, Variance for contourlet transform (CT) and wavelet transform (WT).

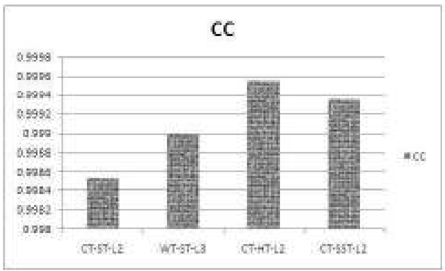

Fig. 7. Statistical feature Correlation Coefficient (CC) for contourlet transform (CT) and wavelet transform (WT).

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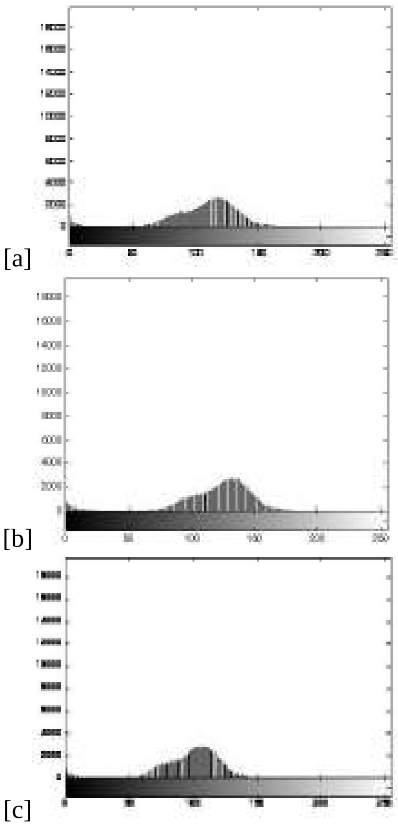

Fig. 8. (a)Histogram of the sample original ultrasound image. (b) Histogram of the sample despeckled image obtained by wavelet transform method. (c) Histogram of the sample despeckled image obtained by proposed method.

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Dr. P. S. Hiremath born in 1952, He received Ph.D. in Applied Mathematics , from Karnataka University, Dharwad, Karnataka, India in 1978. He has completed M.Sc. in Applied Mathematics, Karnataka University, Dharwad, Karnataka, India in 1973. He had been in the Faculty of Mathematics and Computer Science of various institutions in India, namely, National Institute of Technology, Surathkal (1977-79), Coimbatore Institute of Technology, Coimbatore (1979-80), National Institute of Technology, Tiruchinapalli (1980-86), Karnatak University, Dharwad (1986-1993) and has been presently working as Professor of Computer Science in Gulbarga University, Gulbarga (1993 onwards). His research areas of interest are Computational Fluid Dynamics, Optimization Techniques, Image Processing and Pattern Recognition. He has published 130 research papers in peer reviewed International Journals and proceedings of International Conferences.

Prema T. Akkasaligar (ALM2006, AM2005, LM2004,) born in 1971, She is presently pursuing Ph.D. in Computer Science at Gulbarga University, Gulbarga, Karnataka India, since 2008. She received M.E. in Computer Science and Engineering, Gulbarga University, Gulbarga, Karnataka, India in 1999. She recieved Bachelor of Engineering in Computer Science, Karnataka University, Dharwad, Karnataka, India in1995. She is presently working as Assistant Professor at BLDEAs Dr. P.G.Halakatti Engineering College, Bijapur, Karnataka, India. Her research areas are Medical Image Processing and Neural Networks. She has 11 publications in International Journals and proceedings of International Conferences. She is a Life member of Computer Society of India(CSI) since 2006, The Indian Society for Technical Education(ISTE) since 2004, The Institution of Engineers India (IEI) since 2005, International Association of Computer Science and Information Technology (IACSIT) ,Singapore since 2010.

Dr. Sharan Badiger (LM1996,2005,2006,2010) born in 1968, He has completed MD in Internal Medicine, Gulbarga University, Gulbarga, Karnataka, India in 1994. He has completed MBBS, Gulbarga University, Gulbarga, Karnataka, India in 1989. Presently working as Professor of medicine, in the Department of Medicine, Shri. B. M. Patil Medical College , Bijapur, Karnataka, India affiliated to Rajiv Gandhi University of Health Sciences Bangalore, and BLDE University Bijapur, Karnataka, India. His main research interests are in Echocardiography and Imaging in Medicine. He has 14 publications in International/National Journals and Proceedings of the conferences. He is a Life Member of Association of Physicians of India(API) since 1996, Research Society for Studies and Diabetes in India (RSSDI) since 2005, Indian Society of Cardiology (ISC) since 2006, Indian Society of Electrocardiology since 2010, Indian Academy of Geriatrics (IAG) since 2010, International Association of Computer Science and Information Technology (IACSIT) ,Singapore since 2010. Reviewer in 2010 for IJCTE, since 2011 for Bio-Info journal publications and Member of Scientific and Technical Committee and Editorial Review Board on Biological and Life Sciences of WASET journals since 2010. Editor-in-Chief for Journal of Signal and Image Processing, Medical Imaging,International Journal of Medical and Clinical Research, Medical Case Reports and Journal of Infectious Diseases Letters since 2011.

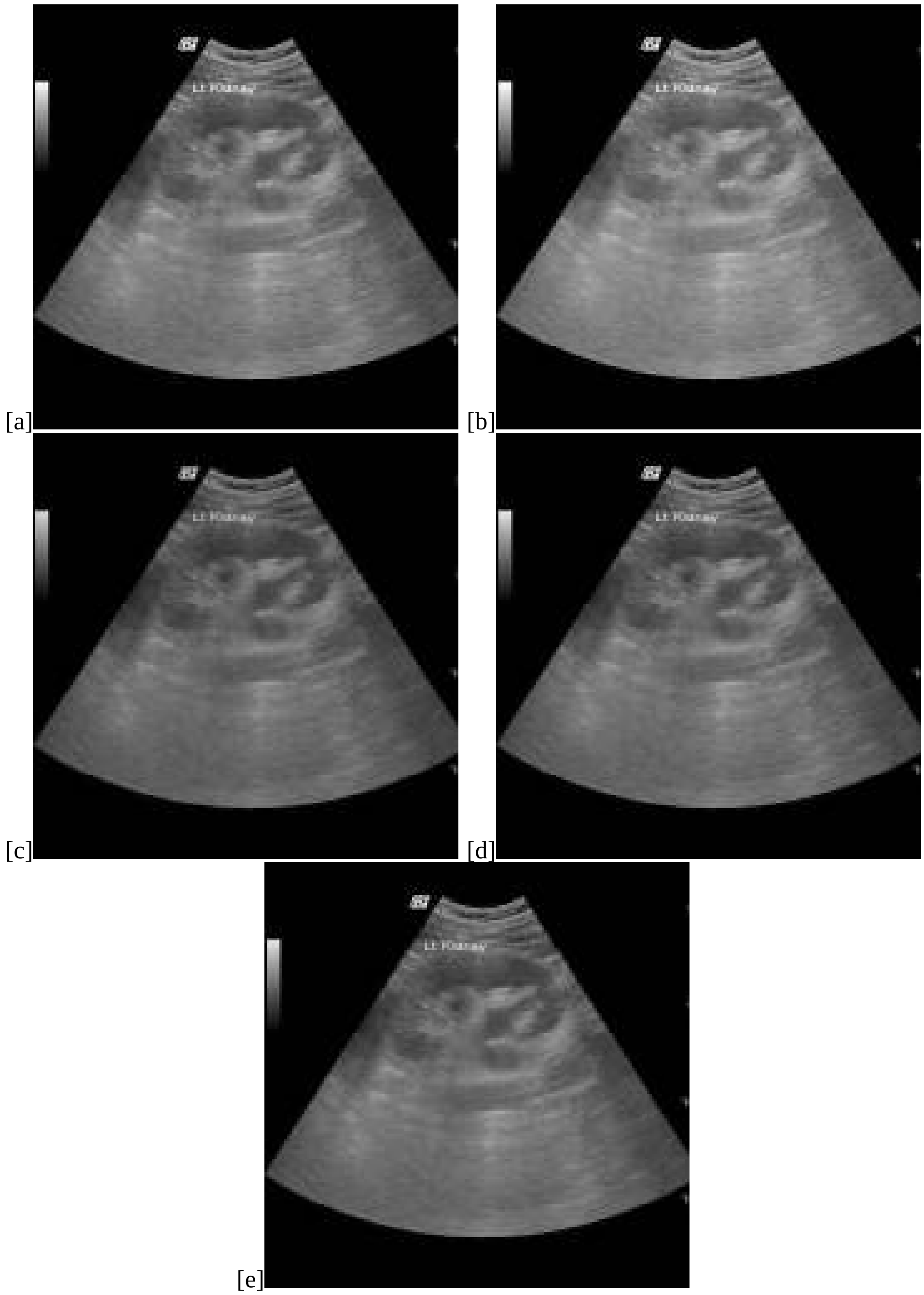

Fig. 9. (a) Original image. (b) Despeckled image using wavelet transform using subband Bayes soft thresholding (level 3). (c) Despeckled image using contourlet transform using soft thresholding. (d) Despeckled image using contourlet transform using hard thresholding (proposed method). (e) Despeckled image using contourlet transform using semi-soft thresholding.