

# Performance Comparison of Wavelet Transform and Contourlet Transform based methods for Despeckling Medical Ultrasound Images

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## ABSTRACT

The widespread usage of ultrasound imaging equipment necessitates the need for better image processing techniques to offer a clearer image to the medical practitioner. This makes the use of efficient despeckle filtering a very important task. The speckle is most often considered a dominant source of multiplicative noise in ultrasound imaging and should be filtered out without affecting important features of the image. The objective of the paper is to compare performance of the multiscale methods, namely, wavelet transform, Laplacian pyramid transform and contourlet transform for despeckling medical ultrasound images. The effects of different thresholding techniques using Bayes shrinkage rule for denoising ultrasound images are examined. The despeckled image quality is evaluated using filter assessment parameters like variance, Mean-Square Error (MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR) and Correlation Coefficient (CC). The performance comparison of multi-scale schemes shows that contourlet transform based despeckling method excels over the other two transform based despeckling methods. Extensive experimentation has been carried out for comparative analysis of performance of the methods.

## General Terms

Image analysis, Noise reduction.

## Keywords

Despeckling, Wavelet transform, Contourlet transform, Laplacian pyramid transform.

## 1. INTRODUCTION

Medical images are usually corrupted by noise during their acquisition and transmission. The main objective of image denoising techniques is to remove such noises while retaining as much as possible the important image features. The use of ultrasound (US) in diagnosis is well established because of its non-invasive nature, low cost, capability of forming real time imaging and continuing improvement in image quality [1]. However, the usefulness of ultrasound imaging is degraded by the presence of signal dependant noise known as speckle. So speckle filtering is a central pre-processing step for feature extraction, analysis and recognition from medical imagery measurements.

The post acquisition techniques for speckle reduction can be classified into two categories: single scale spatial filtering and

transform domain filtering methods. Within the second category, several multiscale methods have been proposed. Recently, there have been many challenges to reduce the speckle noise using Wavelet Transform (WT) as a multiresolution image processing tool. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One widespread method used for speckle reduction is wavelet shrinkage. In [2], a review of despeckling methods for ultrasound imaging is presented. N.K.Ragesh et al. [3] have discussed about two broad categories of noise reduction techniques in ultrasound images namely during acquisition and after acquisition of image. Hiremath et al. [4] have proposed despeckling ultrasound images using wavelet and Bayes thresholding. Alin Achim et al. [5] have presented a novel speckle suppression method for medical ultrasound images. The authors design a Bayesian estimator that exploits speckle statistics. Aleksandra Pizurica et al. [6] have proposed a robust wavelet domain method for noise filtering in medical images. Nikhil Gupta and M.N. Swamy [7] have proposed a novel technique for despeckling the medical ultrasound images using lossy compression and wavelet transform. There has been growing awareness to the observation that wavelet transform is not capable of diagnosing the direction of any line-shaped discontinuity in the image [6]. In essence, wavelets are good at catching zero dimensional singularities, but two-dimensional piecewise smooth signals resembling images have one-dimensional singularities. That is, smooth regions are separated by edges, and while edges are discontinuous across, they are typically smooth curves. Intuitively, wavelets in 2-D obtained by a tensor-product of one dimensional wavelets will be good at isolating the discontinuity across the edge, but will not see the smoothness along the edge. This disappointing behavior indicates that more powerful bases are needed in higher dimensions.

A new nonseparable two-dimensional signal transform, called the Contourlet Transform (CT) has recently been proposed as an alternative to an improvement on separable wavelet for representation of natural images. This transform scales to capture the intrinsic geometrical structure in visual information through a multiresolution, multidimensional decomposition [8]. Mao-Yu Huang et al. [9] 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. [10] have proposed

despeckling medical ultrasound images using contourlet transform using Bayes shrinkage rule. K.Thangavel et al. [11] have compared different filtering techniques based on statistical methods for the removal of speckle noise from ultrasound image of prostate. Wan M.H. et al. [12] have compared performance of five common enhancement techniques based on spatial domain filtering, frequency domain filtering, histogram processing, morphological filtering and wavelet filtering for ultrasound kidney image. Authors show that detection of edge is better by using wavelet filtering and median filtering. Mariana et al. [13] have compared despeckling method, based on wavelet transform, the median filter and the wiener filter for medical ultrasound images. By means of experimental results, it has been shown that the WT method yields far better results than the other two filters. Ali Saad [14] has compared two multi resolution methods: WT and Laplacian pyramid transform (LP), for simultaneous speckle reduction and contrast enhancement for ultrasound images. As a lot of variability exists in ultrasound images, the wavelet method proves to be a much better method than the Laplacian one for an overall improvement. However, a comparison of all the three transforms, namely wavelet transform, Laplacian pyramid transform, and contourlet transform is not found in the literature. In this paper, the aim is to study comparative analysis of the above multiresolution methods for despeckling medical ultrasound images.

## 2. THE TRANSFORM BASED DESPECKLING ALGORITHM

The noise commonly manifests itself as a fine grained structure in an image, which leads to discontinuities at edge points. The transform exploits smoothness of contour effectively by considering a variety of directions following the contours. Further, thresholding is performed so as to reduce speckle. The steps involved in the proposed method are given in the Algorithm 1.

Algorithm 1: Despeckling of 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 wavelet transform on the log transformed image of the Step 2 upto n levels of subband decomposition at each level.

Step 4: Perform thresholding of the transformed image of the Step 3.

Step 5: By performing the inverse transform on the thresholded image of the Step 4, the despeckled image Y is obtained (output image).

Step 6: Compute the values of the performance parameters, namely, variance, MSE, SNR,PSNR, correlation coefficient for the despeckled image Y of the Step 5.

Stop

In the Step 4, the wavelet transformed image can be thresholded by : (i) selecting either global or subband thresholding function, (ii) selecting shrinkage scheme (Hard, Soft or Semi-soft), and (iii) selecting Bayes shrinkage or universal shrinkage rule. However, in the Step 3, the Laplacian pyramidal transform or the contourlet transform can be employed instead of the wavelet transform. The LP transform is performed using different filters upto n levels, where n depends on the image size. 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. This is followed by the thresholding in the Step 4 by selecting shrinkage scheme (Hard, Soft or Semi-soft), and using Bayes shrinkage rule.

## 3. TRANSFORM METHODS

The transform methods are based on the discrete wavelet transform, the Laplacian pyramid transform and the contourlet transform, which are described below:

### 3.1 Discrete wavelet transform

Wavelets have recently emerged as a powerful tool for image denoising. The discrete wavelet transform maps an image into a set of coefficients that constitute a multiscale representation of the image. Discrete Wavelet Transform (DWT) of a signal  $x(n)$  is computed by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response  $g(n)$  giving approximation coefficients. The signal is decomposed simultaneously using a high pass filter  $h(n)$ , giving the detailed coefficients. The low pass filter gives approximation coefficients. These filters are called Quadrature Mirror Filters (QMF). Since half the frequencies of the signal are removed, the filter outputs are down sampled by 2.

$$Y_{low}[k] = \sum_n x[n]g[2k - n] \quad \text{low pass filter output. (1)}$$

$$Y_{high}[k] = \sum_n x[n]h[2k - n] \quad \text{high pass filter output. (2)}$$

Image is a 2D signal represented by  $x(N,M)$ . Each row is filtered and then down sampled to obtain two  $(N,M/2)$  images. Then each column is filtered and down sampled to obtain four  $(N/2,M/2)$  images. The four subbands created are named as LL, LH, HL and HH. In two dimensions, following functions are required: (i) One two-dimensional scaling function  $\varphi(x,y)$ . (ii) Three two-dimensional wavelet functions,  $\psi^H(x,y)$ ,  $\psi^V(x,y)$  and  $\psi^D(x,y)$ . The Approximation subband LL is then decomposed into four at level two and the process can be continued in the same manner for further levels. LL subband has the energy concentration for low pass and the HH band contains high frequency components. Reconstruction can be performed by IDWT (Inverse Discrete Wavelet Transform) to obtain the despeckled image. The despeckling using wavelet coefficients is has been experimented in [4].

### 3.2 Laplacian pyramid transform

One way of achieving a multiscale decomposition is to use a Laplacian pyramid (LP) [15]. The LP decomposition at each level generates a down sampled lowpass version of the original as coarse approximation 'c' and the difference 'd' between the original and the prediction, resulting in a band pass image. The process can be iterated by decomposing the coarse version repeatedly. Assuming the filters in LP are orthogonal filters, an image X is decomposed into J bandpass images  $d_j$ ,  $j=1,2,\dots,J$  and a coarse approximation image  $c_j$ . Then, we have

$$\|X\|^2 = \sum_{j=1}^J \|d_j\|^2 + \|c_j\|^2. \quad (3)$$

The Laplacian is then computed as the difference between the original image and the low pass filtered image. This process is continued to obtain a set of band-pass filtered images (since each one is the difference between two levels of the Gaussian pyramid). Thus the Laplacian pyramid is a set of band pass filters. By repeating these steps several times, a sequence of images are obtained. If these images are stacked one above

another, the result is a tapering pyramid data structure and, hence the name the Laplacian pyramid. This can thus be used to represent images as a series of bandpass filtered images, each sampled at successively sparser densities. A drawback of the LP is the implicit oversampling. However, in contrast to the critically sampled wavelet scheme, the LP has the distinguishing feature that each pyramid level generates only one bandpass image (even for multidimensional cases), which does not have “scrambled” frequencies. This frequency scrambling happens in the wavelet filter bank when a highpass channel, after downsampling, is folded back into the low frequency band, and thus its spectrum is reflected. In the LP, this effect is avoided by downsampling the lowpass channel only.

### 3.3 Contourlet transform

An efficient representation of visual information is one of the important tasks in image processing applications such as denoising. Efficiency of a representation refers to the ability to capture significant information of an object of interest using a small description. Medical ultrasound images are not simply stacks of 1-D piecewise smooth scan-lines. The discontinuity points (i.e. edges) are typically located along smooth curves (i.e. contours) owing to smooth boundaries of physical objects. Thus these images contain intrinsic geometrical structures that are key features in visual information. The wavelets in 2-D are good at isolating the discontinuities at edge points, but will not see the smoothness along the contours. The contourlets can be loosely interpreted as a grouping of nearby wavelet coefficients since their locaters are locally correlated due to the smoothness of the boundary curve. We can obtain a sparse image expansion by first applying a multiscale transform and then applying a local directional transform to gather the nearby basis functions at the same scale into linear structures. Thus, we perform a wavelet like transform for edge detection, and then a local directional transform for contour segment detection. In other words, the contourlet transform comprises a Double Filter Bank (DFB) approach for obtaining sparse expansions for typical images with smooth contours. The contourlet transform is the simple directional extension for wavelet that fixes its subband mixing problem and improves its directionality. The continuous-domain expansion generated by the contourlet construction [16] assumes that the Laplacian pyramid is a multiscale decomposition of the  $L^2(\mathbb{R}^2)$  space into a series of increasing resolution

$$L^2(\mathbb{R}^2) = V_{j_0} \oplus \left( \bigoplus_{j=j_0+1}^{\infty} W_j \right) \quad (4)$$

with the usual definition of the subspaces  $V_{j_0}$  and  $W_j$  as in the wavelet multiresolution analysis:  $V_{j_0}$  is an approximation subspace at the scale  $2^{j_0}$ , whereas  $W_j$  contains the added details to the fine scale  $2^{j-1}$ . In contourlet transform, suppose that an  $l_j$ -level DFB is applied to the detail subspace  $W_j$  of the LP. This results in a decomposition of  $W_j$  into  $2^{l_j}$  directional subspaces at scale  $2^j$ :

$$W_j = \bigoplus_{k=0}^{2^{l_j}-1} W_{j,k}^{l_j} \quad (5)$$

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. The contourlet expansion satisfies the parabolic scaling relation for curves: width  $\propto$  length<sup>2</sup> by using directional decompositions, where

the number of directions is doubled at every other finer scale. Assuming the DFB is orthogonal, it decomposes each bandpass image  $b_j$  into directional coefficients  $d_j$  with  $\|b_j\|^2 = \|d_j\|^2$ . Then the decomposition by PDFB :  $X \mapsto (d_1, d_2, \dots, d_J, a_J)$  also has the energy conservation property :

$$\|X\|^2 = \sum_{j=1}^J \|d_j\|^2 + \|a_J\|^2 \quad (6)$$

## 4. ADAPTIVE THRESHOLDING

The thresholding approach is sensitive to noise components. In this approach, noisy transform coefficients (high frequency components) are attenuated, whose amplitudes are smaller than a certain statistical threshold value, to zero while retaining the smoother transform coefficients to reconstruct the ideal image without much loss in its details. In Soft Thresholding (ST) technique, the input is shrunk to zero by an amount of threshold  $\lambda$ . In Hard Thresholding (HT) technique, the input is preserved if it is greater than threshold  $\lambda$ ; otherwise, it is set to zero. The aim of Semi-Soft Threshold (SST) 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  $\lambda$  and an upper threshold  $\lambda_1$  where  $\lambda_1$  is estimated to be twice the value of lower threshold  $\lambda$ . The criterion of each scheme is described as follows. Given that  $\lambda$  denotes the threshold limit,  $X_w$  denotes the input transform coefficients and  $Y_t$  denotes the output transform coefficients after thresholding, we define the following thresholding functions:

(i) Hard Thresholding

$$Y_t = T_{\text{hard}}(X_w) = \begin{cases} X_w & , \quad \text{where } |X_w| \geq \lambda \\ 0 & , \quad |X_w| < \lambda \end{cases} \quad (7)$$

(ii) Soft Thresholding

$$Y_t = T_{\text{soft}}(X_w) = \begin{cases} \text{sign}\{X_w\}(|X_w| - \lambda) & , \quad \text{where } |X_w| \geq \lambda \\ 0 & , \quad |X_w| < \lambda \end{cases} \quad (8)$$

(iii) Semi-soft Thresholding

$$Y_t = T_{\text{semi-soft}}(X_w) = \begin{cases} 0 & , \quad \text{where } |X_w| \leq \lambda \\ \text{sign}\{X_w\} \frac{\lambda_1(|X_w| - \lambda)}{\lambda_1 - \lambda} & , \quad \text{where } \lambda < |X_w| \leq \lambda_1 \\ X_w & , \quad \text{where } |X_w| > \lambda_1 \end{cases} \quad (9)$$

where  $\lambda_1 = 2\lambda$ .

### 4.1 Bayes shrinkage rule

This shrinkage rule uses a Bayesian mathematical frame work for images to derive subband dependent thresholds. The formula for the threshold on a given subband  $s$  for the model, with zero mean variable  $X$ , is given by

$$\lambda_s = \frac{\sigma_n^2}{\sigma_x} \quad (10)$$

where  $\sigma_n$ , the estimated noise variance found as the median of the absolute deviation of the transform coefficients on the finest level  $L_l$ , is given by

$$\sigma_n = \frac{\text{median}\left(\{|X_{ij}| \in L_l\}\right)}{0.67452} \quad (11)$$

$\sigma_x$ , the estimated signal variance on the sub band considered, is given by

$$\sigma_x = \sqrt{\text{Max}(\sigma_y^2 - \sigma_n^2, 0)} \quad (12)$$

and  $\sigma_y^2$ , an estimate of the variance of the observations, is given by

$$\sigma_y^2 = \frac{1}{N_s} \sum_{k=1}^{N_s} W_k^2 \quad (13)$$

in which,  $N_s$  is the number of the transform coefficients  $W_k$  on the subband considered. In the Eq. 11, 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,  $\lambda_s(\sigma_x) = \max \{X_{i,j} | i \in L_l\}$  and all coefficients are set to zero.

## 5. FILTER ASSESSMENT

To quantify performance improvements of the speckle reduction method, various measures are used. The following metrics are calculated for 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  $\sigma$  is

$$\sigma = \frac{1}{N} \sum_{j=0}^{N-1} X_j^2 \quad (14)$$

**Mean Square Error (MSE):** The MSE measures the quality change between the original image ( $X$ ) and denoised image ( $Y$ ). The average of the squared error measure is given by

$$\text{MSE} = \frac{1}{N} \sum_{j=0}^{N-1} (Y_j - X_j)^2 \quad (15)$$

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 represents the size of the error relative to the signal. We can find the ratio of the average squared value of the source and the MSE as SNR. It is expressed in decibels (dB) as

$$\text{SNR} = 10 \log_{10} \left( \frac{\sigma_g^2}{\sigma_e^2} \right) \quad (16)$$

where,  $\sigma_g^2$  is the variance of the original image and  $\sigma_e^2$  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 represents the size of the error relative to the peak value of the signal than with the size of the error relative to the average squared value of the signal and is computed with the size of the error relative to the average squared value of the signal and is computed as

$$\text{PSNR} = 10 \log_{10} \left( \frac{S^2}{\text{MSE}} \right) \quad (17)$$

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

$$\text{CC} = \frac{N \sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{N \sum X_i^2 - (\sum X_i)^2} \sqrt{N \sum Y_i^2 - (\sum Y_i)^2}} \quad (18)$$

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

## 6. EXPERIMENTATION USING DISCRETE WAVELET TRANSFORM, LAPLACIAN PYRAMID TRANSFORM AND CONTOURLET TRANSFORM

The experimentation has been performed on both the medical ultrasound images and the synthetic images in order to ascertain the effectiveness of the despeckling methods.

### 6.1 Medical ultrasound images

The experimentation is carried out on 52 ultrasound images of size 512 X 512 of kidney using wavelet transform, Laplacian pyramid transform and contourlet transform based despeckling methods. These images are acquired using the instrument GE LOGIQ 3 Expert system with 5-MHz transducer frequency, in JPEG format. The three methods have been implemented on the Core2Duo system with 1GB RAM and 2.53GHz using MATLAB 7.9.

#### 6.1.1 Discrete wavelet transform

In [4], the experimental results show that wavelet transforms can denoise the speckle images more effectively. The main advantage of the wavelet transform is that the image fidelity after reconstruction is visually lossless. Further, it is found that the wavelet filter bior 6.8 with level 3 yields better results than other filters. The performance evaluation of the wavelet method is done in terms of Variance, MSE, SNR, PSNR and CC values computed from the despeckled image. The average results obtained for 52 medical ultrasound images for the different thresholding schemes are given in the Table 1. From Table 1 it is observed that subband threshold function, using Bayes shrinkage rule and soft thresholding technique, gives superior results than other thresholding techniques. The results of wavelet method are compared with common speckle filters, namely the Kuan, Wiener and Lee filters (Figures 1-3). The comparison shows that the wavelet method is better than common speckle filters.

#### 6.1.2 Laplacian pyramid transform

The Laplacian pyramid transform is performed on the log transformed image. The Laplacian pyramidal decompositions up to nine levels are performed using biorthogonal filters with

sufficient accuracy numbers such as the “9/7” and “5/3”. Further, thresholding schemes such as hard thresholding, soft thresholding and semi-soft thresholding is performed to reduce speckle. The threshold value is calculated using Bayes’ shrinkage rule. The Table 2 shows the average results obtained for 52 ultrasound images for different reconstruction methods. The PSNR is calculated up to nine LP decompositions. The PSNR value increases up to 5 decompositions using ST, 2 decompositions using SST and 1 decomposition using HT thereafter reduces. Hence, the optimal level of LP decomposition is 5 for soft thresholding (LP-ST-L5), 2 decompositions for semisoft thresholding (LP-SST-L2) and 1 decomposition for hard thresholding (LP-HT-L1). The optimal reconstruction method is determined by criteria, namely lower variance and MSE, higher SNR and PSNR values, Correlation Coefficient (CC) is nearly equal to one. From Table 2, it is observed that the one level Laplacian pyramidal decomposition using hard thresholding and the filter bior 5/3 yield better results than other techniques. The reconstructed image is the despeckled image.

### 6.1.3 Contourlet transform

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 3, 4 and 5, 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 3, 4 and 5, 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 2<sup>nd</sup> 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

**Table 2. Performance evaluation of different thresholding methods in terms of filter assessment parameters**

Filter type= Bior 5/3					
Levels	PSNR	SNR	MSE	Variance	CC
LP-HT-L1	<b>23.877</b>	<b>18.598</b>	<b>0.0138</b>	<b>0.0160</b>	<b>0.996</b>
LP-ST-L5	20.181	16.792	0.0161	0.0179	0.986
LP-SST-L2	20.9825	17.069	0.0155	0.0169	0.993
Filter type= Bior 9/7					
LP-HT-L1	22.495	16.246	0.019	0.016	0.996
LP-ST-L5	21.328	15.570	0.016	0.016	0.987
LP-SST-L2	20.832	15.964	0.022	0.020	0.992

HT while in ST or SST, coefficients above the threshold are shrunk by absolute value of threshold.

The filter assessment parameters MSE, SNR, PSNR, variance and CC are computed for all the three transforms. The Figures 4-6, shows the comparison of the three methods. From the Figures 4-6, 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 has limited directions (Horizontal, Vertical and Directional). 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. The medical experts performed the visual inspection to confirm the improvement of the image quality attained by the CT algorithm in our experiment.

Another way to analyze the effect of filters is to study the error image between the original image and the filtered image. The error image is calculated as the absolute difference between the two images. The distribution of information inside the error image provides a qualitative indication about the filtering method. If the information is randomly distributed, generally similar to speckle distribution, this indicates that the extracted information from original image is non-structured and may be considered to be mainly noise. If there is some structured information is present in the error image, this indicates that some structured information (boundaries or edges) is higher in one image than other. The difference between the original image and the filtered image proves that edges in the original are higher in amplitude than the filtered image this indicates that a smoothing of edges was obtained. If the opposite case happens, the indication is that a boosting of the edges is present. The error image concerning contourlet transform in the Figure 10 (f) shows clearly that a random distribution of information is present in this figure, which is very similar to speckle distribution. This error image presents a map distribution

**Table 3. Optimal decomposition of LP levels and directional decompositions in terms of variance, MSE, SNR, PSNR, CC values 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	26.743
<b>L2-21</b>	<b>32.770</b>	<b>0.0081</b>	<b>0.00060</b>	<b>0.9995</b>	<b>27.177</b>
L3-521	26.704	0.00882	0.00303	0.9977	25.126
L4-4311	25.391	0.00872	0.00463	0.9973	24.853
L5-51311	25.325	0.00882	0.00470	0.9977	23.823
L6-121311	25.312	0.00982	0.00470	0.9977	21.811

**Table 4. Optimal decomposition of LP levels and directional decompositions in terms of variance, MSE, SNR, PSNR, CC values 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 5. Optimal decomposition of LP levels and directional decompositions in terms of variance, MSE, SNR, PSNR, CC values 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	0.99852	25.269
L3-332	24.575	0.00935	0.01332	0.99358	23.074
L4-5331	24.558	0.00906	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

on every pixel in the image which is much better representation than mean square error or other, generally calculated on the whole image, which is of quite small interest in this type of highly noisy data. This type of error representation proves visually that the edges neither amplified nor damped and the random distribution of noise shows that the filtering reduces mainly the speckle. The error image in the Figure 10 (c) and Figure 10(d) concerning the wavelet transform and Laplacian pyramid transform respectively, shows that some structures(edges) and non-structures (mainly noise) information are amplified in these images. Figure 10(d) concerning the wavelet transform and Laplacian pyramid transform respectively, shows that some structures(edges) and non-structures (mainly noise) information are amplified in these images. This is due to the boosting of local strong variation without taking into account the directionality as in contourlet. The qualitative assessment and quantitative viewpoints shows that despeckling using contourlet transform is better adapted to ultrasound images.

## 6.2 Synthetic image

It is very difficult to compare three methods for removing speckle from real ultrasound images, because it depends on what we need from such an image. For small details it is not obvious to a non-expert in the diagnoses of ultrasound images to know what we need to eliminate or to preserve and enhance. Some of the statistical measurements such as SNR, MSE, CC are not very significant in the case of real ultrasound images if they are applied to whole image without a prior knowledge of it. Such measurements could be efficient in the case of simulated images. In order to investigate the quantitative performance of the selected methods, an image with artificial speckle noise was employed. A purely synthetic image which consists of regions with uniform intensity, sharp edges and strong scatters with SNR of 8.3dB is considered for experimentation (image available at <http://telin.ugnet.be/~sanja>). The experimentation is carried out on synthetic image to evaluate despeckle filtering in medical ultrasound imaging. All the three despeckling methods, namely, wavelet transform, Laplacian pyramid transform and contourlet transform are performed on the phantom image. All the filters show the similar performance in removing the speckle at the same time gave significant results. From the Figures.7-9, it is observed that despeckling using contourlet transform gave very good performance in terms of (i) decreasing the variance, (ii) increasing the SNR, PSNR and CC values to be nearly equal to one. Further, it is found that, 4-level of Laplacian pyramidal decomposition and 14 directional bandpass subbands (4 of 32X32, 4 of 64 x 64 , 2 of 128 x 256, 4 of 256X256) using soft thresholding with Bayes shrinkage rule yields optimal results for speckle reduction. From Figure 11 (a), (c), (e), the edges of the phantom image was studied and it was shown that the contourlet transform based despeckling method does not blur edges as with the other two despeckle filtering techniques. The error image in Figure 11 (b) and (d), obtained after wavelet transform and Laplacian pyramid transform shows that structured information and nonstructured information are amplified (white pixels) in these images. This is due to the boosting of local strong variation without taking into account the edge direction as in contourlets (Figure 11 (f)). It is clear that despeckling using contourlet transform is better interms of smoothing the internal variations and preserving boundaries.

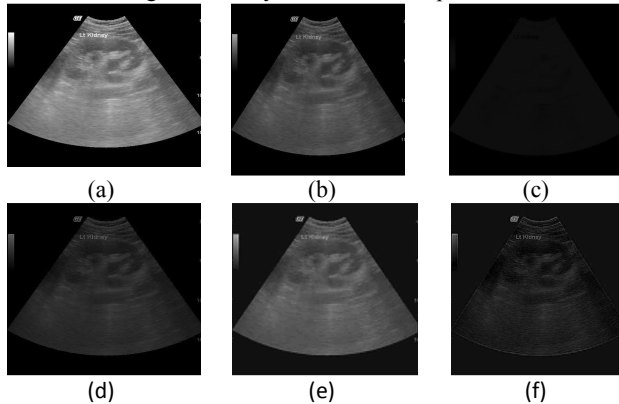
## 7. CONCLUSION

In this paper, three multi-scale methods are tested and compared for despeckling medical ultrasound images. These methods are proven to be very efficient to treat multiplicative noise and reduce speckle in ultrasound images. Several studies prove that wavelet based despeckling is among the best methods for ultrasound images. The Laplacian pyramid transform and contourlet transform based despeckling methods are applied recently on ultrasound images and proves to give very good results. But the wavelet transform, Laplacian pyramid transform and contourlet transform have not been compared to each other using ultrasound images, where lot of variations exists in the background. The performance evaluation of the three methods is done interms of variance, MSE, SNR, PSNR correlation coefficient (CC) are computed from despeckled image. This study proves that contourlet transform using hard thresholding is an excellent tool for despeckling medical ultrasound images. Further, it is found that, 2-level of Laplacian pyramidal decomposition and 6 directional bandpass subbands (4 of 64 x 64, 2 of 128 x 256) using hard thresholding with Bayes' shrinkage rule yields optimal results for speckle reduction. The

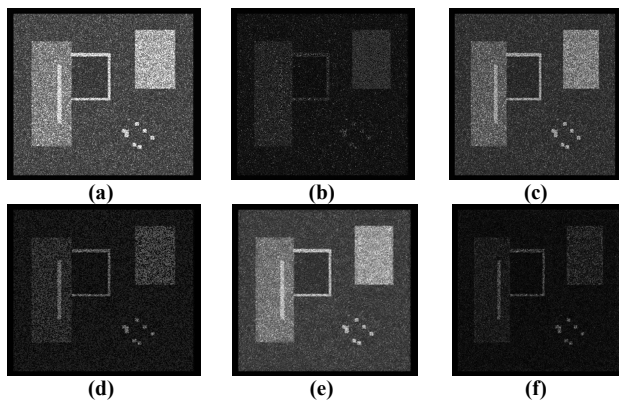
error distribution indicates that the contourlet scheme provides a better overall improvement. The contourlet transform based despeckling method produces better quality ultrasound images for subsequent computer-assisted image analysis by medical experts.

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**Fig.10 (a) Despeckled image using wavelet transform (b) Despeckled image using Laplacian pyramid transform (c)The difference image of original image and Fig. 10(a). (d) The difference image of original image and Fig. 10(b). (e) Despeckled image using contourlet transform (f) The difference image of original image and Fig.10 (e)**



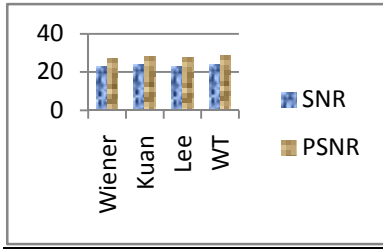
**Fig. 11. (a) Despeckled image using wavelet transform (b) The difference image of original image and Fig. 11 (a). (c) Despeckled image using Laplacian pyramid transform (d) The difference image of original image and Fig. 11 (c). (e) Despeckled image using contourlet transform (f) The difference image of original image and Fig.11 (e)**

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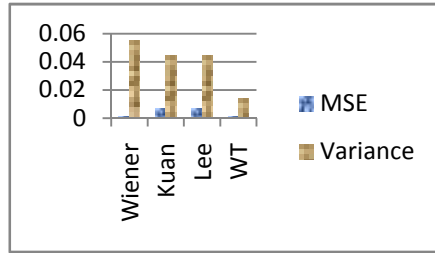
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**Table 1. Performance evaluation of different thresholding methods in terms of variance, MSE, SNR, PSNR, CC values.**

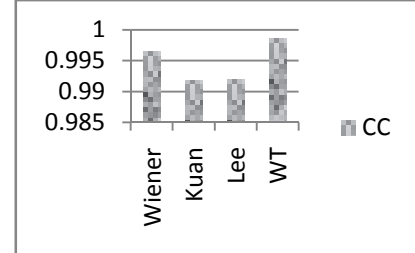
Shrinkage rule	Thresholding	Global thresholding(2)					Subband thresholding(1)				
		variance	MSE	SNR	CC	PSNR	variance	MSE	SNR	CC	PSNR
Bayes shrinkage (2)	Hard(1)	0.0552	0.00137	23.95	0.99613	26.6934	0.0237	0.0014	24.8	0.998	27.513
	Soft(2)	0.0552	0.00137	23.95	0.99613	26.6934	0.0138	0.0012	24.811	0.999	28.66
	Semi-soft(3)	0.0552	0.00139	23.98	0.99613	25.93	0.0268	0.0014	24.78	0.998	27.722
universal shrinkage (1)	Hard(1)	0.0248	0.0057	18.28	0.9933	21.3518	0.0288	0.0056	20.28	0.996	20.827
	Soft(2)	0.0142	0.0164	13.83	0.9875	17.7381	0.0214	0.0085	16.74	0.994	18.198
	Semi-soft(3)	0.0198	0.0094	16.04	0.9919	17.0855	0.0262	0.0073	18.984	0.995	19.612



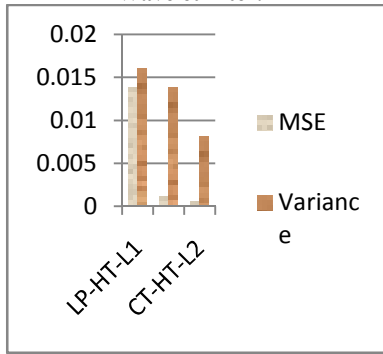
**Fig. 1. Statistical features PSNR and SNR for common speckle filters and Wavelet filter.**



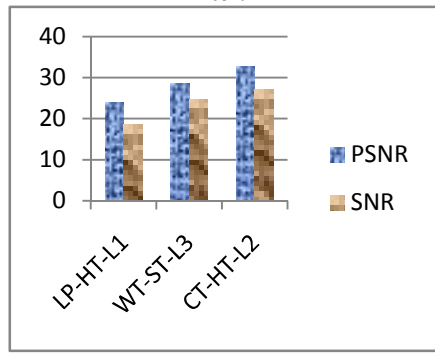
**Fig. 2. Statistical features Variance, MSE for common speckle filters and Wavelet filter.**



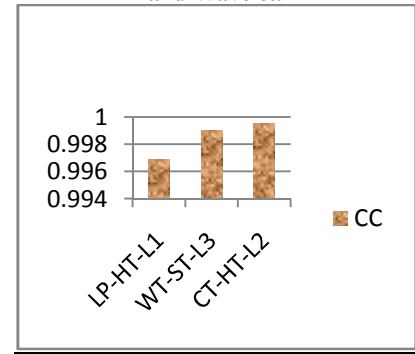
**Fig. 3. Statistical feature Correlation Coefficient (CC) for common Speckle filters and Wavelet.**



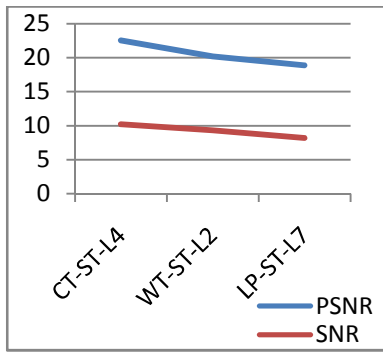
**Fig. 4. Statistical feature MSE, Variance for CT, LP and WT for US images.**



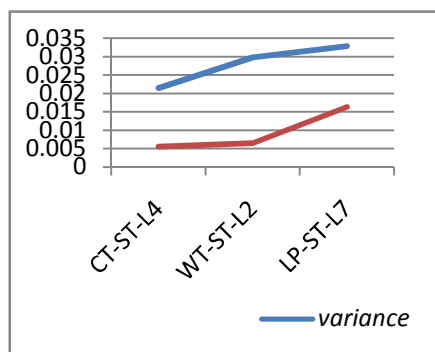
**Fig. 5. Statistical feature PSNR, SNR for CT, LP and WT for US images.**



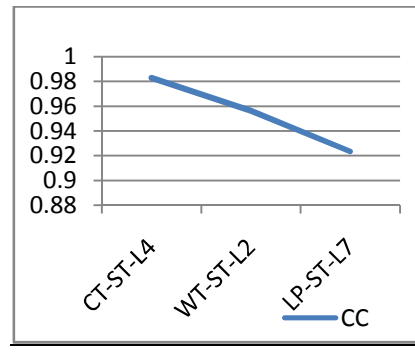
**Fig. 6. Statistical feature Correlation Coefficient (CC), for CT, LP and WT for US images.**



**Fig. 7. Statistical feature PSNR, SNR for CT, LP and WT for Synthetic image.**



**Fig. 8. Statistical feature MSE, Variance for CT, LP and WT for Synthetic image.**



**Fig. 9. Statistical feature Correlation Coefficient (CC), for CT, LP and WT for Synthetic image.**