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Comparative Performance Analysis of Speckle Reduction Using Curvelet and Contourlet Transform forMedical Images

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Abstract: The random speckle noise in the obtained fetal ultrasound images is caused by the interference of reflected ultrasound wave fronts. The presence of speckle noise will reduce the quality of the image and even hide image details that affect the processing of image segmentation, feature extraction and recognition and most importantly disease diagnosis. The standard measurements from the fetal ultrasound images will help the physicians to make correct diagnosis. The accuracy of diagnosis is feasible only the image is noise free. Hence performing filter of the speckle noise is very important. The proposed technique of contourlet transform performs better edge preserving filter compared to other speckle reducing anisotropic diffusion filters and curvelet transform. Contourlet transform is to obtain the number of levels of Laplacian pyramidal decomposition and the number of directional decompositions to perform on each pyramidal level and thresholding strategy which yields optimal despeckling of medical ultrasound images, in particular. The proposed method involves the log transformed original ultrasound image being subjected to contourlet transform, to obtain contourlet coefficients. The experiment result indicates the contourlet denoising suppresses the noise effectively in both of quantitative and visual means by producing high PSNR.

Key words: SRAD · Curvelet Transform · Contourlet Transform

INTRODUCTION

Ultrasound imaging have major part in medical imaging due to its non-invasive nature, accurate, low cost, potential of forming real time image, harmless to the human beings and continuing improvement in image quality. It is applied for imaging soft tissues on organs likes spleen, uterus, liver, heart, kidney, brain etc. Speckle is found in ultrasound image and other coherent image modalities. It is caused by the constructive and destructive coherent interferences of back scattered echoes that are much smaller than the spatial resolution of medical ultrasound system. Speckle pattern is a construction of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters. Ultrasonography is most commonly utilized diagnostic imaging modality in obstetrics and gynecology. The ultrasound imaging is an important role to monitor the growth of the fetus and estimating the fetal biometrics [1]. Ultrasonography processes the images in real time and is the most widely preferred imaging technique because of its noninvasive, low cost and portable properties. In recent years, the qualities of information from the ultrasound device have been increased due to the growth on technology. However, speckle is a primary source of noise in the clinical ultrasound imaging system and much affects the quality of the ultrasound images. Medical images are usually corrupted by noise during their acquisition and transmission. The ultrasound imaging is degraded by the presence of s ignal dependent noise known as speckle. So speckle filtering has become a central pre-processing step for feature extraction, analysis and recognition from medical imagery measurements. The post-acquisition methods for speckle reduction can be classified into two categories are single scale spatial filtering and transform domain filtering methods. In the second category, several multi scale methods have been proposed. Recently, it has much challenge to reduce the speckle noise using Wavelet Transform (WT) as a multi resolution image processing tool [2]. Speckle noise is a high-frequency component of the image and determine in

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wavelet coefficients. One widespread technique used for speckle reduction is wavelet shrinkage. In reality, wavelets are fine at catching zero dimensional singularities, but two-dimensional piecewise smooth signals resembling images have one-dimensional singularities. Smooth regions are separated by edges and it is discontinuous across, they are typically smooth curves.

Intuitively, wavelets in 2-D obtains a tensor-product of one-dimensional wavelets have been good at isolating the discontinuity across the edge and it will not see the smoothness along the edge. This disappointing manner indicates that stronger bases are needed in higher dimensions. Speckle noise [3, 5] present in medical ultrasound images will reduce the contrast and image resolution which attack the diagnostic value of the ultrasound imaging. It obscures and blurs image detail significantly, reduces the image quality. Hence decreases the difficulty for the observer to differentiate fine detail of the image during diagnostic examination and also reduces the speed and accuracy of ultrasound image processing functions such as segmentation and registration. Therefore, always a speckle reduction is an important prerequisite for ultrasound image processing tasks. Speckle noise attacks all coherent imaging modalities and makes it difficult to perform further processing. It is produced by the constructive and destructive interference of back scattered coherent waves from the transducer at different phases. Speckle is a random multiplicative noise and it affects the extraction and interpretation of fine parts in the image. Hence speckle reduction methods have to be applied to reduce the noise proportion in ultrasound images as well as increase the visual quality of images. However, the goal of denoising process is used to remove the speckle without damaging the clinically significant features. Curvelet transform which represent a new multiscale directional transform to the 2D ultrasound images involving curved edges. This technique is capable of representing edges and curved shapes with effective. Hence the curvelet denoising method is appropriate for the fetal abdominal ultrasound images involving curved structures. Contourlets have feature to preserving edges and fine details in the image [6]. The encoding complexity in proposed method is less when compared to tree structured quantization. As well the shift-invariance has been recognized that an efficient image representation was account for the geometrical structure extensive in natural scenes. In this case, several representation schemes have been proposed recently. Contourlet transform is a multidirectional and multiscale transform which is constructed by combining the Laplacian pyramid, with the directional filter bank (DFB) proposed.

Proposed Method: Following steps are obtained by denoising algorithm of proposed method: 1) Compute all thresholds for proposed method; 2) Compute norm; 3) Apply curvelet and contourlet transform to noisy image; 4) Apply hard thresholding to the coefficients; and 5) Apply inverse curvelet and contourlet transform.

Figure 1 shows the proposed method of curvelet and contourlet transform in denoising of the images. In denoising using contourlet was carried out with inverse wrapping function, involving a decomposition level of 8. Hard thresholding is applied to coefficients after the decomposition. A value of thrice the standard deviation was used as the threshold. Coefficients exceeding the chosen threshold were rejected. The image was reconstructed from the remaining coefficients. Denoising the images using wavelet transform was carried out with symlet 4 wavelet, which is an integralpart from the wavelet tool box. The four types of noises are Random noise, Gaussian noise, Salt and Pepper noise and Speckle noise, were chosen for mixing with the ultrasonic image. The quality of reconstructed image is usually specified in terms of peak signal to noise ratio (PSNR).

Perfomance Comparison: The Figure 2 shows the performance evaluation technique used to compare the SRAD with proposed method. PSNR values shows the better denoising method when the value is high.

MRI Image: Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging method uses radiology to analyses the anatomy and physiology of the body in both health and disease. MRI scanner has used magnetic fields and radio waves to form images of the body.

Ultrasonic Image: The ultrasound imaging is very important role in monitoring the growth of the fetus and estimating the fetal biometrics. Ultrasonography processes the images in real time and is the most widely present in imaging technique because of its noninvasive, low cost and portable properties.

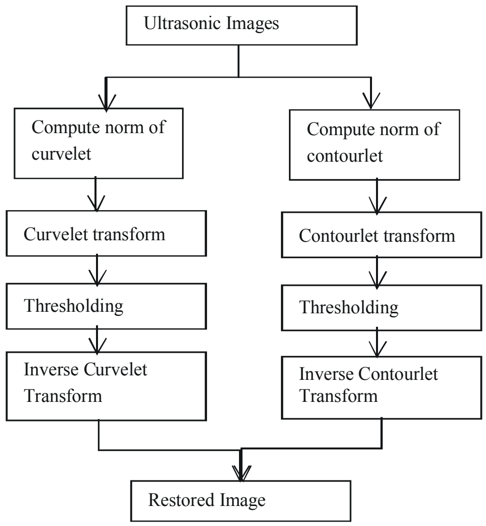


Fig. 1: Block diagram for proposed method

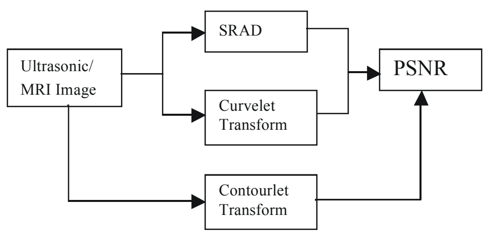


Fig. 2: process of performance comparison

SRAD: Speckle reducing anisotropic diffusion (SRAD) stands for speckle reducing anisotropic diffusion. The SRAD method uses only a template of four closest neighbours of the pixel under consideration to achieve the diffusion process. SRAD not only preserves edges, but also enhances edges by inhibiting diffusion across edges and enable diffusion on either side of the edge [7]. It is adaptive in nature and hard thresholding was not use to alter the process in smooth regions or in regions near edges.

Curvelet Transform: The curvelet analysis is depended on wavelet analysis, but it is more effective incurved structure imagings. The process of curvelet denoising is beginning by transforming the speckle affected image into a new space.

Contourlet Transform: It is a new two-dimensional transform technique for image representations. The Contourlet transform has properties of multiresolution, localization, directionality, critical sampling and anisotropy. Its basic functions are multiscale and multidimensional. Contours of original images, which are the superior features in natural images, can be captured effectively by the few coefficients using Contourlet transform.

Mean Square Error: The MSE evaluates the quality of an estimator or predictor and shown in Equation 1.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[I(i,j) - K(i,j) \right]^2 \tag{1}$$

PSNR: PSNR is the most widely used quality metric and higher its value indicates the better denoising algorithm. It measures the ratio of peak signal in the image to noise and also the difference between images. The PSNR values were calculated using the following Equation 2:

$$\text{PSNR} = 10\log_{10} 255^2/\text{MSE} \tag{2}$$

Despeckling Techniques

SRAD Filter: SRAD is a Partial Differential Equation (PDE) technique to spackle removal in images. It produce the image scale space (a set of filter imaging that vary from fine to coarse) without bias depends on the filter window size and shape. SRAD is an anisotropic diffusion technique for smoothing speckled imagery [8]. The intensity image ????$_0$ (????) have finite power and no zero values above the image support Ù, the output image I(x, y; t) is measured according to the following PDE is mention in Equation 3.

$$\begin{Bmatrix} \dfrac{\partial I(x,y;t)}{\partial t} = div[c(q)\Delta I(x,y;t))] \\ I(x,y;0) = I_0(x,y), \left(\dfrac{\partial I(x,y;t)}{\partial \vec{n}} \right) | \, \partial\Omega = 0 \end{Bmatrix} \tag{3}$$

The diffusion coefficient $c(q)$ of the SRAD process is defined as;

$$c(q) = \frac{1}{1 + \dfrac{\left[q^2(x,y;t) - q_0^2(t) \right]}{\left[q_0^2(t)\left(1 + q_0^2(t)\right) \right]}} \tag{4}$$

Or

$$c(q) = \exp\left\{ - \frac{\left[q^2(x,y;t) - q_0^2(t) \right]}{\left[q_0^2(t)\left(1 + q_0^2(t)\right) \right]} \right\} \tag{5}$$

In Equation 4 and 5, q(x, y; t) is the instantaneous coefficient of variation determined by:

$$q(x,y;t)=\sqrt{\frac{\left(\frac{1}{2}\right)\left(\frac{|\Delta|}{I}\right)^2-\left(\frac{1}{4^2}\right)\left(\frac{\Delta^2 I}{I}\right)^2}{\left[1+\left(\frac{1}{4}\right)\left(\frac{\Delta^2 I}{I}\right)\right]^2}} \quad (6)$$

The SRAD I nstantaneous coefficient of variation q(x, y; t) serves as the edge detector in spackled imagery as shown in Equation 6. The function exhibit it's higher value at edge or on higher in contrast features and produces low values in homogenous regions. The improvement reflects encouraging isotropic diffusion in homogenous regions of the image where q(x, y; t) fluctuates around ????$_0$ (????). The speckle scale function ????$_0$(????) effectively controls the amount of smoothing implemented to the image by SRAD. It is estimated using Equation 7.

$$q_0(t)=\frac{\sqrt{var[z(t)]}}{\overline{z(t)}} \quad (7)$$

where var[z(t)] and ??(??) are the intensity variance and mean over a homogenous area at t, respectively.

Curvelet Transform Despeckling: The curvelet analysis is based on the wavelet analysis, but this is more suitable for images with curved structures. The procedure for curvelet denoising is initiated by transform of the affected speckle image into a new space [9]. In that, the curvelet coefficients where the signal to noise ratio is greater are retained and those with low signal to ratio are reduced. The utilized coefficients are transformed back to the original space to obtain the despeckled image. The curvelet decomposition required the following steps,

- The Subband decomposition of an image f is decomposed into subbands and it is determined in Equation 8.

$$f \to (P_0 f, \Delta_1 f, \Delta_2 f, \Delta_3 f, \ldots.) \quad (8)$$

- Each subband in an image is smoothly partitioned into a block of an appropriate scale and the resulting block is renormalized to a unit scale.
- Finally, ridgelet analysis of each block is analyzed by using the digital ridgelet transform. The curvelet coefficients are analysed to remove the noisy coefficients by setting a threshold. The processes are repeated in the reverse order to perform inverse curvelet transform. The curvelet transform required only the lesser number of nonzero coefficients for the image reconstruction.

Contourlet Transform Despeckling: The Contourlet transform [10] is a directional transform which is capable of detecting contour and fine details in an image. This process in the transformation starts with the discrete domain construction and then sparse expansion in the continuous domain. The difference between Contourlet and other transformations is that the Laplacian pyramid along with the Directional Filter Banks is used. In result, it is not only detects the edge discontinuities, but also transforms all these discontinuities into continuous domain. The Figure 3 shows the Contourlet Transformation, in which the input image contains of frequency components like LL (Low Low), LH (Low High), HL (High Low) and HH (High Low). The Laplacian Pyramid at each level constructs a Low pass output (LL) and a Band pass output (LH, HL and HH). The Band pass output is then proceeding into Directional Filter Bank which results in Contourlet coefficients. The Low pass output is again proceeding through the Laplacian Pyramid to obtain more coefficients and this is done till the fine details of the image are obtained.In general image denoising is to convert the noisy image into a transformation domain such as Contourlet and then compare the transform coefficients with a fixed threshold. This method constructs discrete domain multiresolution and multi direction using nonseparable filter banks and resulted in flexible multiresolution, local and directional image extension using contour sectors and so named Contourlet transform. The contourlet transform construction has been divided into two parts: (1) A pyramid structure which ensures the multiscale property and (2) DFB structure which gives directionality.

Pyramid: The shift sensitivity of the LP have remedied by replacing it with a 2-channel 2-D filter bank structure. Such expansion is similar to the 1-D a trous wavelet expansion Shensa (1993) and has a redundancy of J + 1 when J is the number of decomposition stages. The ideal frequency assist the low-pass filter at the j-th stage is the Region shown in Equation 9.

$$\left[-\frac{\pi}{2^j},\frac{\pi}{2^j}\right]*\left[-\frac{\pi}{2^j},\frac{\pi}{2^j}\right] \quad (9)$$

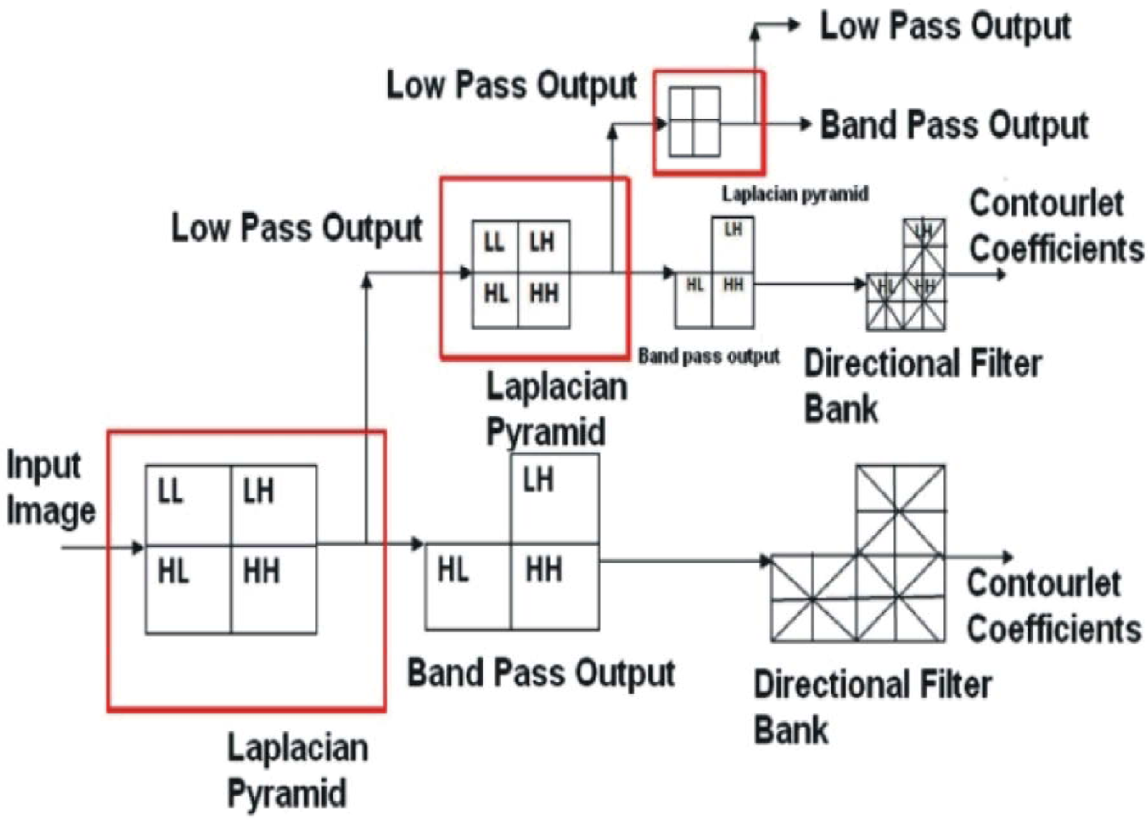


Fig. 3: Block diagram of contourlet transform

Hence, the support of the high-pass filter is the complement of the low-pass support region on the square as mentioned in Equation 10.

$$\left[-\frac{\pi}{2^{j+1}},\frac{\pi}{2^{j+1}}\right]*\left[-\frac{\pi}{2^{j+1}},\frac{\pi}{2^{j+1}}\right] \quad (10)$$

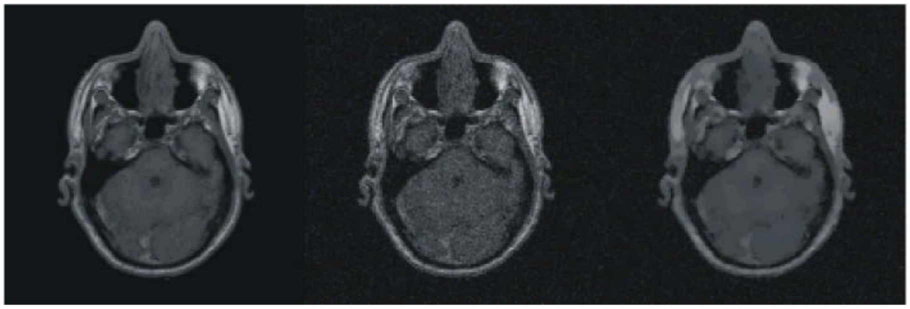
The proposed structure is thus different from the tensor product, a trous algorithm. It has j+1 redundancy. By variation, the 2-D a trous algorithm has 3j+1 redundancy.

Directional Filter Bank: The directional filter bank is established by combining critically sampled fan filter banks and pre/post re-sampling operations. It produces a tree-structured filter bank which splits the frequency plane into directional wedges. A fully shift-invariant directional expansion is achieved by simply switching off the downsamplers and upsamplers in the DFB equivalent filter bank. Because of multirate identities, it is equivalent to switching off each of the downsamplers in the tree structure, while still supervision the re-sampling operations that can be absorbed by the filters. This results in a tree structure composed of two-channel filter banks.

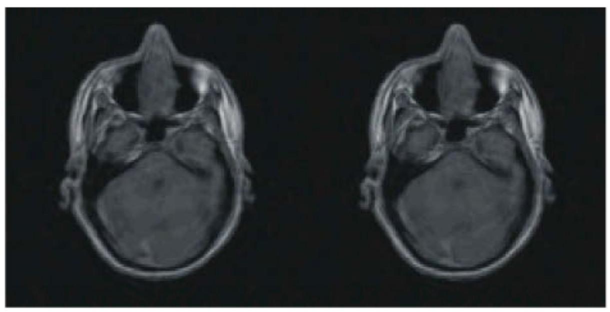
Expremental Result: The MRI and Ultrasonic image are taken as an input images. A section size of 256 × 256 is chosen for the experiments.The Figure 4(a) is an input brain image of MRI and Figure 5(a) & 6(a) are the input ultrasonic image presence of foetus and cardiac image of foetus. Presences of speckle noise in images are representing in figure 4(b), 5(b) & 6(b). The comparative output of SRAD filter, Curvelet transform and contourlet transform denoising are shown in Figure 4[(c), (d), (e)], 5[(c), (d), (e)] and 6[(c), (d), (e)] respectiveley. Evaluation graph for MSE and PSNR are plotted in Figure 4[(f), (g)], 5[(f), (g)] & 6[(f), (g)] for comparative denoising ouputs. As shown in Table 1 the values of PSNR is used to determine best technique. It measures the ratio of peak signal in the image to noise and also the difference between images. The higher value indicates the better denoising technique. And the MSE is used to determine the quality of predicted image.

Table 1: MSE and PSNR measurement of proposed method

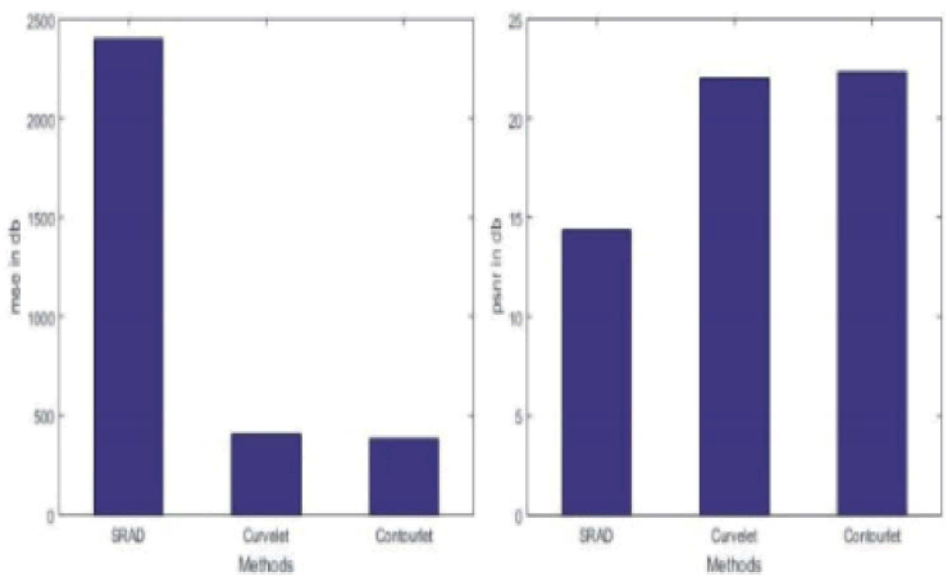
	SRAD		Curvelet Transform		Contourlet Transform	
Medical images	MSE	PSNR	MSE	PSNR	MSE	PSNR
Figure 4 (MRI)	2411.02	14.34	405.41	22.09	380.78	22.36
Figure 5 (ultrasonic)	3415.86	12.83	450.42	21.63	400.20	22.14
Figure 6 (ultrasonic)	2240.16	14.66	469.27	21.45	415.80	21.98



(a) (b) (c)



(d) (e)



(f) (g)

Fig. 4: (a) MRI image, (b) Speckle noise image, (c) SRAD filter, (d) Curvelet Transform, (e) contourlet Transform, (f) MSE Graph, (g) PSNR Graph

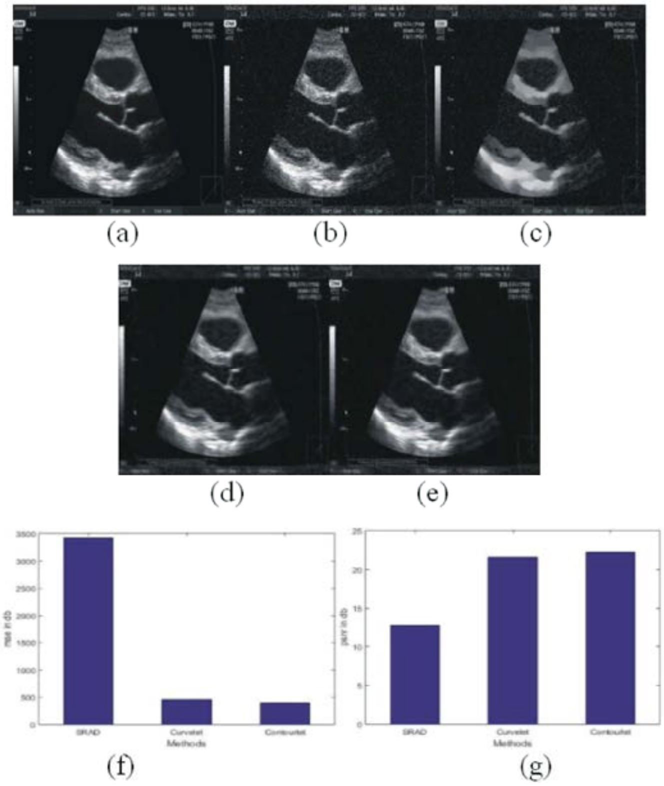


Fig. 5: (a) Ultrasonic image, (b) Speckle noise image, (c) SRAD filter, (d) Curvelet Transform, (e) contourlet Transform, (f) MSE Graph, (g) PSNR Graph

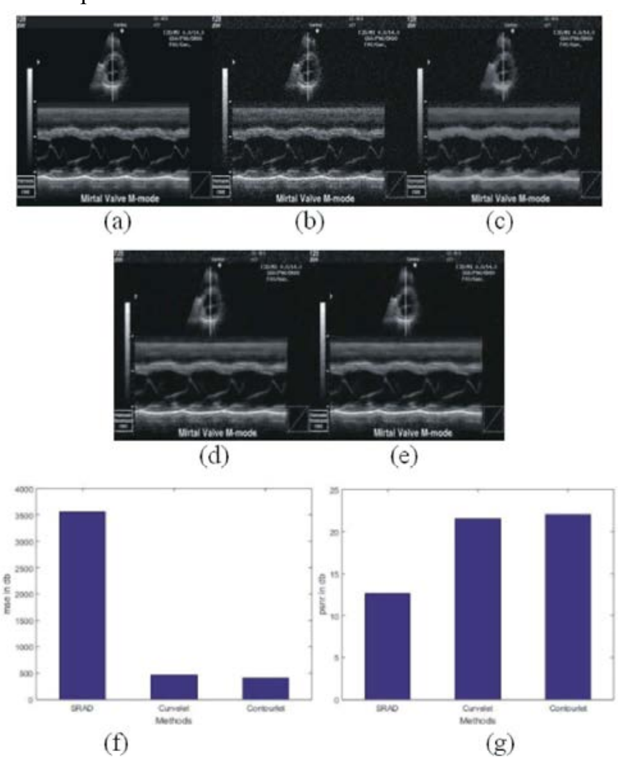


Fig. 6: (a) Ultrasonic image, (b) Speckle noise image, (c) SRAD filter, (d) Curvelet Transform, (e) Contourlet Transform, (f) MSE Graph, (g) PSNR Graph

CONCLUSION

The obtained results indicate that the contourlet transform performs efficient despeckling for the images involving curved structures, multiscale and multidimensional. The visual quality of the image is also enhanced and the measured quality metrics show that the curvelet transform method has high PSNR. The contourlet transform based despeckling method produces greater quality ultrasound images for subsequent computer assisted image analysis. The contourlet transform is directly defined on the digital friendly discrete rectangular grids. Since contourlets overcome the limitations of wavelets and curvelets it will be better suited for speckle reduction of ultrasound medical images. The accurate determination of the fetal biometric parameters helps in the monitoring of fetal growth and early diagnosis of fetal malformations.

REFERENCES

1. Christoph B. Burckhardt, 2005. “Speckle in ultrasound B-mode scans”, IEEE Transactions on Sonics and Ultrasonics, 25(1): 1-6.
2. Sivakumar, R. and D. Nedumaran, 2010. “Comparative study of Speckle Noise Reduction of Ultrasound B-scan Images in Matrix Laboratory Environment”, International Journal of Computer Applications, 10(9): 46-50.
3. Joel, T. and R. Sivakumar, 2013 “Despeckling of Ultrasound Medical Images: A Survey”, Journal of Image and Graphics, 1(3).
4. Michailovich, O.V. and A. Tannenbaum, 2006. “Despeckling of Medical Ultrasound Images”, IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, 53(1): 64-78.
5. Nithya, J. and M. Madheswaran, 2015. “Fetal ultrasound image denoising using curvelet transform”, ICTACT Journal On Image And Video Processing, 05(03): 951-955.
6. Cao Xuhui, Li Lei, Li Hui and Bai Peirui, 2013. “Ultrasound Image Denoising Based on the Contourlet Transform and Anisotropic Diffusion”, International Conference on Image and Graphics, pp: 73-77.
7. Venkata Rukmini, C.H., 2000. “Filter Selection for Speckle Noise Reduction”, Dissertation Thesis, Thapar University.
8. Yu, Y. and S.T. Acton, 2002. “Speckle reducing anisotropic diffusion”, IEEE Transactions on Image Processing, 11(11): 1260-1270.
9. Starck, J.L., E.J. Candès and D.L. Donoho, 2002. “The curvelet transform for image denoising”, IEEE Transactions on Image Processing, 11(6): 670-684.
10. Jayachandiran Jai Jaganath Babu, Gnanou Florence Sudha, 2014. “Non-subsampled contourlet transform based image denoising in ultrasound thyroid images using adaptive binary morphological operations”, IET Computer Vision, 8(6): 718-728.