A Research Paper On Reducion Of Speckle Noise In Ultrasound Imaging Using Wavelet And Contourlet Transform

[1] MR. HITESH S. ASARI, [2]ASS.PROF. AMI SHAH

[1]M.E.[Signal Processing And Communication] Student, Department Of Electronics and Communication, A.D. Patel institute and Technologey, New Vallabh Vidhyanagar, Anand
[2]Asst.Professor, Department Of Electronics and Communication, A.D. Patel institute and Technologey, New Vallabh Vidhyanagar, Anand

hitesh.asari@gmail.com, amipatira06@gmail.com

Abstract—*Ultrasound is a medical imaging technique that is widely used for diagnostic purposes. Ultrasound is used for x-ray and ultrasonography. A major problem regarding these images is in their inherent corruption by speckle noise. The presence of speckle noises severely hampers and the interpretation and analysis of medical ultrasound images. There are many algorithms are proposed for reducing the mixer of noise in medical ultrasound images. In this paper, speckle noise removed is done by methods based on wavelet transform and counterlet transform. The two proposed alternative methods are evaluated and compared in terms of filter assessment parameters namely peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Mean Square Error (MSE), Variance and Correlation Coefficient(CC). At last this method compare wavelet and counterlet transforms and see which better transform is.*

Keywords—-speckle noise,contourlet transform, logarithmic thresholding , ultrasonic images, wavelet transform.

I. INTRODUCTION

Ultrasound or ultrasonography is a medical imaging technique that uses high frequency sound waves and their echoes, Known as a "pulse echo technique". The technique is similar to the echolocation used by bats, whales and dolphins, as well as SONAR used by submarines etc.

Medical imaging is an important source of diagnosing the malfunctions inside human body. Some crucial Medical imaging instruments are X-ray, Ultrasound, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). Medical ultrasound imaging is one of the significant techniques in detecting and visualizing the hidden body parts. There could be distortions due to improper contact or air gap between the transducer probe and the human body. Another kind of distortion that may occur during ultrasound imaging is due to the beam forming process and also during the signal processing stage. In order to overcome through various distortions, image processing has been successfully used. Image processing is a significant technique in medical field, especially in surgical decisions. Converting an image into homogeneous regions has been an area of hot research from a decade, especially when the image is made up of complex textures. Various techniques have been proposed for this task, including spatial frequency techniques. Image processing techniques have been used widely depending on the specific application and image modalities. Computer based detection of abnormal growth of tissues in a human body are preferred to manual processing methods in the medical investigations because of accuracy and satisfactory results. Several methods for processing the ultrasound images have been developed.

A major problem regarding these images is in their inherent corruption by speckle noise. The presence of speckle noise severely hampers the interpretation and analysis of medical ultrasound im ages. The objective of the report is to propose a method for removal of noise in the medical ultrasound images. The image noise content is assumed to be the mixture of speckle and Gaussian noise. Two alternative algorithms are proposed for reducing the mixed noise in medical ultrasound images. While speckle noise removal is done by method based on wavelet transform (WT), Laplacian pyramid transform (LP) or contourlet transform (CT), the Gaussian noise component is reduced by Gaussian filter either in the preprocessing or post processing stage. The two proposed alternative methods are evaluated in terms of filter assessment parameters namely Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Mean Square Error (MSE), Variance and Correlation Coefficient (CC). The experimental results show that Gaussian filter in preprocessing stage is found to be effective in despeckling based on Laplacian pyramid transform and contourlet transform.[1]

II. WAVELET TRANSFORM

Wavelets convert the image into a series of wavelets that can be stored more efficiently than pixel blocks. Although wavelets also have rough edges, they are able to render pictures better by eliminating the "blockiness" that is a common feature of DCT based compression. Not only does this make for smoother color toning and clearer edges where there are sharp changes of color, it also gives smaller file sizes than a JPEG image with the same level of compression.

A. *One-Dimensional Discrete Wavelet Transform*

Two main methods exist for the implementation of 1D-DWT:

i. The traditional convolution-base the implementation

ii. The lifting-based implementation

B. *Two-The 2-D Discrete Wavelet Transform*

The 2-D DWT operates in a straightforward manner by inserting array transposition between the two 1-D DWT. Dimensional Discrete Wavelet Transform. The rows of the array are processed first with only one level of decomposition. This essentially divides the array into two vertical halves, with

i. The first half storing the average coefficients,

ii. While the second vertical half stores the detail coefficients.

This process is repeated again with the columns, resulting in four sub-bands. The result is shown in Figure 1 and is decomposed into four quadrants with different interpretations. Human visual system is very much sensitive to low frequency and hence, the decompose data available in the lower sub-band region and is selected and transmitted, information in the higher sub-bands regions are rejected depending upon required information content.

LL: The upper left quadrant consists of all coefficients, which were filtered by the analysis low pass filter ĥ along the rows and then filtered along the corresponding columns with the analysis low pass filter ĥ again. This sub block is denoted by LL and represents the approximated version of the original at half the resolution.

HL/LH: The lower left and the upper right blocks were filtered along the rows and columns with ĥ and ĝ, alternatively. The LH block contains vertical edges, mostly. In contrast, the HL block shows horizontal edges very clearly.

HH: The lower right quadrant was derived analogously to the upper left quadrant but with the use of the analysis high pass filter ĝ which belongs to the given wavelet. We can interpret this block as the area, where we find edges of the original image in diagonal direction.

The two dimensional wavelet transform can be applied to the coarser version at half the resolution, recursively, in order to further decorrelate neighboring pixels of the input image. So the image can be shown as below[3].

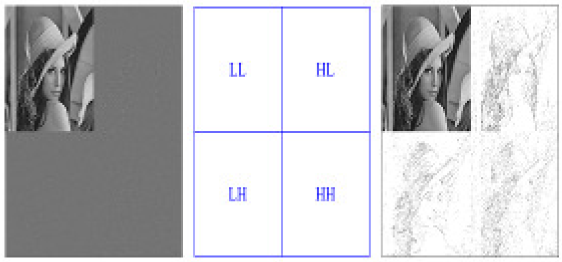
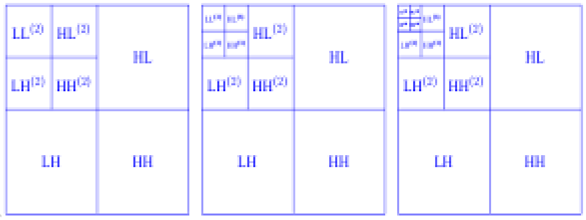


Fig. 1 one dimensional CDF (2,2) wavelet transform applied to the rows of the benchmark image lena with reflection at the image boundaries[3]

Since we have restricted the images to be of quadratic size N = 2^l for l ∈ N, we can perform at most $l = \log_2 N$ levels of transform. Thereafter the coefficient in the upper left corner represents the average grey scale value of the whole image and is called DC coefficient (DC : direct current). In practice, usually four up to six level of wavelet transform level will be performed.



(a) Two levels (b) Three levels (c) Four levels

2D-DWT

Fig. 2 Multi resolution scheme after several levels of wavelet transform[3]

III. CONTOURLET TRANSFORM

Image processing typically relies on simple statistical models to characterize images. Natural images tend to have certain common characteristics that make them look "natural."

The major drawback for wavelets in two-dimensions is their limited ability in capturing directional information. To overcome this deficiency, researchers have recently considered multiscale and directional representations that can capture the intrinsic geometrical structures such as smooth contours in natural images.

In particular, the curvelet transform, pioneered by Cand`es and Donoho, was shown to be optimal in a certain sense for functions in the continuous domain with curved singularities.

Inspired by curvelets, Do[7] and Vetterli[7], developed the contourlet transform based on an efficient two-dimensional multiscale and directional filter bank that can deal effectively with images having smooth contours. Contourlets not only possess the main features of wavelets (namely, multiscale and time-frequency localization), but also offer a high degree of directionality and anisotropy.[4]

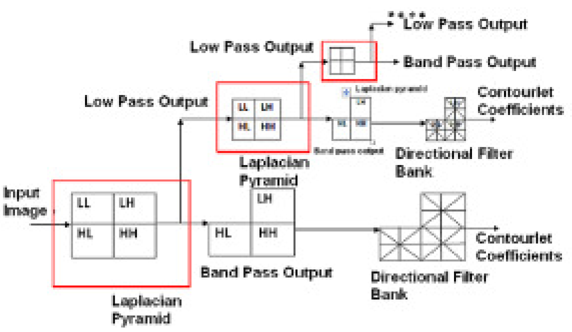


Fig. 3 Contourlet Transform [5]

The Laplacian Pyramid at each level generates a Lowpass output (LL) and a Band pass output (LH, HL, and HH). The Band pass output is then passed into Directional Filter Bank, which results in contourlet coefficients . The Low pass output is again passed through the Laplacian Pyramid to obtain more coefficients and this is done till the fine details of the image are obtained.[5]

.

Contourlets were developed as an improvement over wavelets in terms of this inefficiency. The resulting transform has the multiscale and time-frequency-localization properties of wavelets, but also offers a high degree of directionality and anisotropy. Specifically, contourlet transform involves basis functions that are oriented at any power of two's number of directions with flexible aspect ratios. With such a rich set of basic functions, contourlets can represent a smooth contour with fewer coefficients compared with wavelets

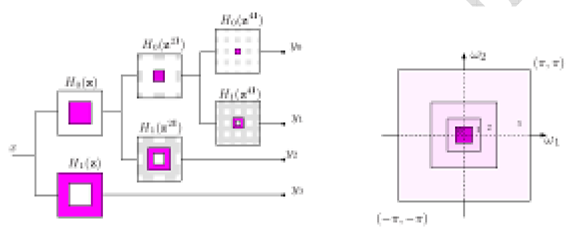


Fig. 4 Directional Filter Bank [6]

The Nonsubsampled Pyramid (NSP): What gives the multi-scale property of the NSCT is a shift-invariant filtering structure that achieves a subband decomposition similar to that of the Laplacian pyramid. Our solution is obtained by using two-channel nonsubsampled 2-D filter banks. Figure 4 illustrates the proposed nonsubsampled pyramid (NSP) decomposition with J = 3 stages. Such expansion is conceptually similar to the 1-D nonsubsampled wavelet transform computed with the J + 1 redundancy, where J denotes the number of decomposition stages. The ideal passband support of the low pass filter at the j-th stage is the region $\left[-\frac{\pi}{2^j},\frac{\pi}{2^j}\right]^2$. Accordingly, the ideal support of the equivalent highpass filter is the complement of the lowpass, i.e., the region

$$\left[-\frac{\pi}{2^{j-1}},\frac{\pi}{2^{j-1}}\right]^2 / \left[-\frac{\pi}{2^j},\frac{\pi}{2^j}\right]^2$$

The filters for subsequent stages are obtained by upsampling the filters of the first stage. This gives the multi-scale property without the need for additional filter design. The proposed structure is thus different from the separable nonsubsampled wavelet transform (NSWT). In particular, one bandpass image isproduced at each stage resulting in J + 1 redundancy. By contrast, the separable NSWT produces three directional images at each stage resulting in 3J + 1 redundancy.

The proposed pyramid is not the only 2-D pyramid with redundancy. The 2-D pyramid proposed in is obtained with a similar structure. Specifically, the NSFB of is built from a given low pass filter $H_0(z)$. One then sets $H_1(z) = 1 - H_0(z)$, and $G_1(z) = 1 - G_0(z)$. This perfect reconstruction system can be seen as a particular case of our more general structure. The advantage of our construction is that it is less restrictive and as a result, better filters can be obtained[6]

IJKRECE

IV Algorithms for removing speckle noise:

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. The signal at the output of the ultrasound imaging system may be defined as[3]

g(i,j) = f(i,j)u(i,j) + n(i,j) (1)

where,

g(i,j)= the noisy pixel in the image;

f(i,j) = noise free pixel;

u(i,j)= multiplicative noise;

n(i,j) = additive noise;

i,j = are the indices of the spatial locations that belong to the 2D space of real numbers, i, j ∈ R^2.

The speckle noise becomes very close to the white Gaussian noise corresponding to the uncompressed Rayleigh signal. 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) (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)) (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

A. For wavelet transform

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.

B. For contourlet transform

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 directional 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 threshold 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.

In the Step 4, the wavelet or contourlet transformed image can be threshold by :

I. Selecting either global or subband thresholding function,
II. Selecting shrinkage scheme (Hard, Soft or Semi-soft),
III. Selecting Bayes shrinkage or universal shrinkage rule.[4]

ADAPTIVE THRESHOLDING

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. 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. we define the following thresholding functions:

Hard thresholding:

$$Y_t = \begin{cases} X_w & if\ |X_\omega| >= 0 \\ 0 & if\ |X_\omega| < 0 \end{cases}$$

(4)

Soft thresholding

$$Y_t = \begin{cases} [\![sign\{X\}]\!]_w\}(|X_\omega| - \lambda) & if\ |X_\omega| >= \lambda \\ 0 & if\ |X_\omega| < \lambda \end{cases}$$

(5)

Semi-soft thresolding

$$Y_t = \begin{cases} 0 & if\ |X_\omega| <= \lambda \\ \dfrac{[\![sign\{X\}]\!]_w\}(\lambda_1(|X_\omega| - \lambda))}{\lambda_1 - \lambda} & if\ \lambda < |X_\omega| <= \lambda_1 \\ X_\omega & if\ |X_\omega| > \lambda_1 \end{cases}$$

(6)

Shrinkage rule

Bayes shrink has been proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name Bayes shrinks. 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

$$\lambda_s = \frac{\sigma_n^2}{\sigma_x}$$

(7)

where, the estimated noise variance found as the median of the absolute deviation of the contourlet coefficients on the finest level L1 , is given by

$$\sigma_n = \frac{median\ (\{|\ x_{i,j} \in L_1\})}{0.67452}$$

(8)

The value 0.67452 is the median absolute deviation of normal distribution with zero mean and unit variance. The estimated signal variance on the sub band considered, is given by

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

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

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

(10)

Where

N_s =number of the counterlet coefficient

W_k =subband consideration

FILTER ASSESSMENT:

The quality of an image is examined by objective evaluation as well as subjective evaluation.

JIKRECE

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.

1. Noise variance : It determines the contents of the speckle in the image.

$$\sigma = \frac{1}{N}\sum_{j=0}^{N-1} x_j^2$$

(11)

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

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

(12)

3. 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

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

(13)

Where

σ_g^2 =Difference between the original and denoised image.

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

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

(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.

5. Correlation Coefficient (CC): It represents the strength and direction of a linear relationship between two variants. 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

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

(15)

If the correlation coefficient is near to +1, then there exists stronger positive correlation between the original and despeckled image.[4]

V RESULTS

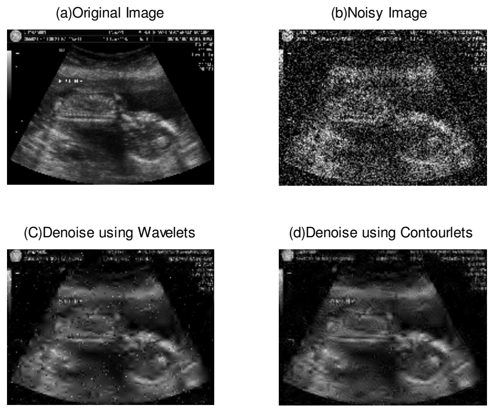


Fig.5 (a) original image (b) noisy image with variance 0.7
(c) Wavelet denoising (d) contourlet denoising with logarithmic threshold

TABLE I. COMPARISION RESULTS BETWEEN WAVELET TRANSFORM AND CONTOURLET TRANSFORMS WITH LOGARITHMIC THRESHOLD, FOR A ABOVE IMAGE.

Noice variance	Wavelet Transform			Contourlet transform		
	MSE	SNR	PSNR	MSE	SNR	PSNR
0.4	0.001	27.44	76.34	0.002	21.44	74.49
0.5	0.002	23.81	74.92	0.003	19.30	73.39
0.7	0.003	18.92	72.96	0.004	16.28	72.05
1	0.005	14.40	70.93	0.005	13.76	70.78
3	0.019	8.300	65.17	0.013	8.260	66.95

CONCLUSION

Wavelets transform and contourlets transform makes sharp boundary of natural image. So they are used for the remove speckle noise in ultrasound image. They are used for compression and make boundary sharp so everyone can detect the boundary of image. As shown in figure 5 and results of SNR in table contourlet transform has more SNR than wavelet so contourlet is better than wavelet.

REFERENCES

[1] "Performance Comparison of Wavelet Transform and
Contourlet Transform based methods for Despeckling
Medical Ultrasound Images"*by P.S. Hiremath, Prema T. Akkasaligar, and Sharan Badiger.* International

JIKRECE

Journal of Computer Applications (0975 – 8887) Volume 26– No.9, July 2011

[2] "Implementation of Discrete Wavelet Transform Processor For Image Compression Processor For Image Compression" by Ms.Yamini S.Bute, Prof. R.W. Jasutkar international Journal of Computer Science and Network (IJCSN),Volume 1, Issue 3, June 2012 www.ijcsn.org

[3] "wavelet transforms on image", thesis report, unpublished.

[4] "Directional Multiscale Modeling of Images using the Contourlet Transform" by Duncan D.-Y. Po and Minh N. Do, Member, IEEE.

[5] "Medical Image Denoising Using Adaptive Threshold Based On Contourlet Transform" S.Satheesh , Dr.KVSVR Prasad. Advanced Computing: An International Journal (ACIJ), Vol.2, No.2, March 2011

[6] Minh *N. Do, Member, IEEE, and Martin Vetterli, Fellow,* IEEE ,The Contourlet Transform: "An Efficient Directional Multiresolution Image Representation". IEEE TRANSACTIONS ON IMAGE PROCESSING

[7] "Speckle Reducing Contourlet Transform for Medical Ultrasound Images" by *P.S. Hiremath, Prema T. Akkasaligar and Sharan Badiger,* International Journal of Computer and Information Engineering 4:4 2010

[8] Mersad Mirzavandi, Mehran Yazdi, : "A Logarithmic Threshold Contourlet Based Method for Speckle Noise Reduction Of Medical Ultrasound Images ,Canadian Journal on Image Processing and Computer Vision Vol. 3 No. 1, March 2012.

[9] "The Nonsubsampled Contourlet Transform:" Theory, Design, and Applications,IEEE" Arthur L. Cunha, Student Member, IEEE, Jianping Zhou, Student Member, IEEE , and Minh N. Do, Member, IEEE. IEEE TRANSACTIONS ON IMAGE PROCESSING, MAY 20

[10]"Implementation of Discrete Wavelet Transform Processor For Image Compression Processor For Image Compression" by Ms.Yamini S.Bute, Prof. R.W. Jasutkar Dept of CSE,,G.H. Raisoni College of Engg Nagpur Dept CSE G.H. Raisoni College of, Engg Nagpur. International Journal of Computer Applications (0975 – 8887) Volume 1, June 2012

[11] . "A New Contourlet Transform With Sharp Frequency Localization unplished", Yue Lu and Minh N. Do, www.ifp.uiuc.edu

[12] "Performance Comparison of Wavelet Transform and Contourlet Transform based methods for Despeckling Medical Ultrasound Images", by P.S. Hiremath, Prema T. Akkasaligar, and Sharan Badiger. International journal of computer science. July 2011.

[13] "Speckle Noise Reduction of Medical Ultrasound Images using Bayesshrink Wavelet Threshold" by K. Karthikeyan and Dr. C. Chandrasekar , International Journal of Computer Applications, May 2011.

[14] "Speckle Noise Reduction in Ultrasound Images by Wavelet Thresholding" by Ms. Alka Vishwa and Ms. Shilpa Sharma, February 2012. www.ijarcsse.com

[15] "Wavelet Transform In Image Recognition" by Aleˇs Proch´ azka, Andrea Gavlasov´ a, and Karel Volka, IEEE.

[16] "contourlet" by M. N. Do and M. Vetterli. IEEE.

JIKRECE