Analysis of Various Parameters of Filters (Wavelets) with Curvelet Transform for Denoising in Ultrasound Images

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ABSTRACT
Ultrasonography is considered to be one of the most powerful techniques for imaging organs and soft tissue structures in human body. It is preferred over other medical imaging methods because it is non-invasive, portable, and versatile and does not use ionising radiations. Despite their obvious advantages, ultrasound (US) images are contaminated with multiplicative noise called 'speckle' which is one of the major sources of image quality degradation. In the medical literature, speckle has been treated as a distracting artifact as it tends to degrade the resolution and the object detectability. Image denoising is used to remove the noise while retaining as much as possible the important signal features. The purpose of image denoising is to estimate the original image form the noisy data. Image denoising is still remains the challenge for researchers because noise removal introduces artifacts and causes blurring of the images.

Keywords: Speckle noise, Denoising, Simulation, Blurred, Speckle reduction.

1.INTRODUCTION

1.1 Ultrasound Images
Ultrasonography is considered to be one of the most powerful techniques for imaging organs and soft tissue structures in human body.

Despite their obvious advantages, ultrasound(US) images are contaminated with multiplicative noise called 'speckle' which is one of the major sources of image quality degradation.

In the medical literature, speckle has been treated as a distracting artifact as it tends to degrade the resolution and the object detectability. Moreover, in US images the speckle noise has a spatial correlation length on each axis, which is same as resolution cell size. This spatial correlation makes the speckle suppression a very difficult and delicate task, hence, a trade-off has to be made between the degree of speckle suppression and feature preservation.

1.2 Speckle Noise
Speckle significantly degrades the image quality and hence, makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. Speckle is a form of multiplicative noise, which makes visual interpretation difficult. Laser holography and ultrasound imaging are two techniques susceptive to speckle degradation. Speckle noise causing greater degradation within bright areas of an image than in dark areas.

1.3 Image Denoising
Image denoising is used to remove the noise while retaining as much as possible the important signal features. The purpose of image denoising is to estimate the original image form the noisy data. Image denoising is still remains the challenge for researchers because noise removal introduces artifacts and causes blurring of the images.

2. LITERATURE SURVEY
A new multiscale non-linear method for speckle suppression in ultrasound images is presented. The main innovation is the use of realistic distributions of the wavelet coefficients. By combining these distributions with a simple shrinkage function (soft-thresholding), a closed-form expression for soft thresholding is derived analytically. [1]

A new and efficient technique for despeckling medical US images has been proposed, which relies on the Rayleigh distribution of speckle noise and Gaussian prior for modelling the wavelet coefficients in a logarithmically transformed US image. [2]

????.....This work describes the implementation, testing and evaluation of popular denoising algorithms for the denoising of low-field MR images. [3]

For Medical field denoising, an image prior model was purposed using Markov Random Field. The parameters on the model are learned from PCA and MLE. Based on this model, image denoising can be done by Bayesian analysis. [4]

A simple and subband adaptive threshold is proposed to address the issue of image recovery from its noisy counterpart. It is based on the generalized Guassian distribution modeling of subband coefficients. The image denoising algorithm uses soft thresholding to provide smoothness and better edge preservation at the same time. [5]

A strategy for digitally implement both the ridgelet and the curvelet transforms. Curvelet thresholding rivals sophisticated techniques that have been the object of extensive development over the last decade. [6]

Curvelets provide a powerful tool for representing very general linear symmetric systems of hyperbolic differential equations. [7]

A novel implementation of the discrete curvelet transform is proposed in this work. The transform is based on the Fast Fourier Transform (FFT) and has the same order of complexity as the FFT. The discrete curvelet functions are defined by a parameterized family of smooth windowed functions that are 2-pi periodic and form a partition of unity. The transform is named the Uniform Discrete Curvelet Transform (UDCT) because the centers of the curvelet functions at each resolution are located on a uniform grid. [8]

?????...A new approach for SAR image enhancement and change detection based on the curvelet transform has been proposed and applied to TerraSAR-X data of the city center of Munich. [9]

An adaptive threshold estimation method for image denoising in the curvelet domain by using mean, (Spatial Frequency Measure) SFM and (Difference Operator)DOP, experiment work on Lena, cameraman and boat gray test images at different type of noises (Random, Salt & pepper ,Gaussian ,Speckle) showed that the proposed adaptive threshold method success to estimate and reduce noise from image and it is more effective at reduce noise from image than (Rudin-Osher-Fatemi) ROF filter and Non Local Mean algorithm. The proposed adaptive estimation method introduced betterresults than (Rudin-Osher-Fatemi) ROF filter, Non Local Mean algorithm and Wiener filter at reduce noise (Random, Salt & pepper, Gaussian) according to increasing of PSNR values of enhanced images by 0.044 at Random, 1.05 at salt &pepper and 0.457 at Gaussian noise. [10]

3. TECHNIQUES FOR DENOISING

3.1 Curvelet Transform Techniques

Curvelet Transform is a new multi-scale representation most suitable for objects with curves. Developed by Candès and Donoho (1999).

A discontinuity point affects all the Fourier coefficients in the domain. Hence the FT doesn't handle point's discontinuities well. Using wavelets, it affects only a limited number of coefficients. Hence the WT handles point discontinuities well. Discontinuities across a simple curve affect all the wavelets coefficients on the curve. Hence the WT doesn't handle curves discontinuities well. Curvelets are designed to handle curves using only a small number of coefficients. Hence the CvT handles curve discontinuities well.

The Curvelet Transform includes four stages:

- Sub-band decomposition
- Smooth partitioning
- Renormalization
- Ridgelet analysis

3.1.1 Algorithm

1. Sub-band decomposition

$$f \mapsto \left(P_0 f, \Delta_1 f, \Delta_2 f, \ldots\right)$$

- Dividing the image into resolution layers.
- Each layer contains details of different frequencies:
  - P_0 – Low-pass filter.
  - Δ_1, Δ_2, … – Band-pass (high-pass) filters.
- The original image can be reconstructed from the sub-bands:

$$\|f\|_2^2 = \|P_0 f\|_2^2 + \sum_s \|\Delta_s f\|_2^2$$

Energy preservation

$$f = P_0\left(P_0 f\right) + \sum_s \Delta_s\left(\Delta_s f\right)$$

- Low-pass filter Φ_0 deals with low frequencies near $|\xi| \le 1$.
- Band-pass filters Ψ_{2s} deals with frequencies near domain $|\xi| \in [2^{2s}, 2^{2s+2}]$.
- Recursive construction – $\Psi_{2s}(x) = 2^{4s}\Psi(2^{2s}x)$.
- The sub-band decomposition is simply applying a convolution operator:

$$P_0 f = \Phi_0 * f \qquad \Delta_s f = \Psi_{2s} * f$$

- The sub-band decomposition can be approximated using the well known wavelet transform:
  - Using wavelet transform, f is decomposed into S_0, D_1, D_2, D_3, etc.
  - $P_0 f$ is partially constructed from S_0 and D_1, and may include also D_2 and D_3.
  - $\Delta_s f$ is constructed from D_{2s} and D_{2s+1}.

2. **Smooth partitioning**

- A grid of dyadic squares is defined:

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in \mathbf{Q}_s$$

- $\mathbf{Q}_s$ – All the dyadic squares of the grid.
- Let w be a smooth windowing function with 'main' support of size $2^{-s} \times 2^{-s}$.
- For each square, w_Q is a displacement of w localized near Q.
- Multiplying $\Delta_s f$ with w_Q ($\forall Q \in \mathbf{Q}_s$) produces a smooth dissection of the function into 'squares'.

- The windowing function w is a nonnegative smooth function.

$$h_Q = w_Q \cdot \Delta_s f$$

- Partition of the energy:
  - The energy of certain pixel (x_1, x_2) is divided between all sampling windows of the grid.

$$\sum_{k_1,k_2} w^2(x_1-k_1, x_2-k_2) \equiv 1$$

- Reconstruction:

$$\sum_{Q\in\mathbf{Q}_s} w_Q \cdot h_Q = \sum_{Q\in\mathbf{Q}_s} w_Q^2 \cdot h = h$$

- Parserval relation:

$$\sum_{Q\in\mathbf{Q}_s} \|h_Q\|_2^2 = \sum_{Q\in\mathbf{Q}_s} \int w_Q^2 \cdot h^2 = \int \sum_{Q\in\mathbf{Q}_s} w_Q^2 \cdot h^2 = \int h^2 = \|h\|_2^2$$

3. Renormalization

- Renormalization is centering each dyadic square to the unit square $[0, 1] \times [0, 1]$.
- For each Q, the operator T_Q is defined as:

$$(T_Q f)(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

- Each square is renormalized

$$g_Q = T_Q^{-1} h_Q$$

4. Ridgelet analysis

A) Before ridgelet transform:

- The Δ_s f layer contains objects with frequencies near domain $|\xi| \in [2^{2s}, 2^{2s+2}]$.
  - We expect to find ridges with width $\approx 2^{-2s}$.
- Windowing creates ridges of width $\approx 2^{-2s}$ and length $\approx 2^{-s}$.
- The renormalized ridge has an aspect ratio of width $\approx$ length^2.
- We would like to encode those ridges efficiently
  - Using the **Ridgelet Transform**
- Ridgelet are an orthonormal set $\{\rho_\lambda\}$ for $L^2(\Re^2)$
- Divides the frequency domain to dyadic coronae $|\xi| \in [2^s, 2^{s+1}]$.
- In the angular direction, samples the s-the corona at least 2^s times.
- In the radial direction, samples using local wavelets.
- The ridgelet element has a formula in the frequency domain:

where,

$$\hat{\rho}_\lambda(\xi) = \tfrac{1}{2}|\xi|^{-\frac{1}{2}}\left(\hat{\psi}_{j,k}(|\xi|)\cdot \omega_{i,l}(\theta) + \hat{\psi}_{j,k}(-|\xi|)\cdot \omega_{i,l}(\theta+\pi)\right)$$

- $\omega_{i,l}$ are periodic wavelets for $[-\pi, \pi)$.
- i is the angular scale and $l \in [0, 2^{i-1}-1]$ is the angular location.
- $\psi_{j,k}$ are Meyer wavelets for $\Re$.
- j is the ridgelet scale and k is the ridgelet location.

Ridgelet transform:

- Each normalized square is analyzed in the ridgelet system:

$$\alpha_{(Q,\lambda)} = \langle g_Q, \rho_\lambda \rangle$$

  - The ridge fragment has an aspect ratio of $2^{-2s} \times 2^{-s}$.
  - After the renormalization, it has localized frequency in band $|\xi| \in [2^s, 2^{s+1}]$.
  - A ridge fragment needs only a very few ridgelet coefficients to represent it.

3.2 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is introduced to overcome the redundancy problem of CWT. The approach is to scale and translate the wavelets in discrete steps.

$$\mathrm{DWT}(\tau_0, s_0) = \frac{1}{\sqrt{s_0^f}} \int_{-\infty}^{\infty} f(t)\, \psi\left(\frac{t - k\tau_0 s_0^f}{s_0^f}\right) dt \qquad (3.1)$$

Where s_0^f is the scaling factor τ_0 is the translating factor, k and j are just integers.

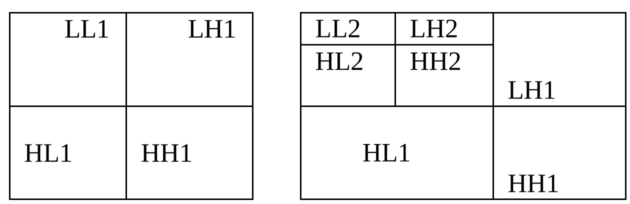
Subsequently, we can represent the mother wavelet in term of scaling and translation of a dyadic transform as

$$\psi_{j,k}(t) = 2^{-f/2}\psi(2^{-f}t - k) \qquad (3.2)$$

Replacing eqn, the coefficients of DWT can be represented as

$$C_{f,k} = 2^{-f/2} \int_{-\infty}^{\infty} f(t)\psi(2^{-f}t - k)\, dx \qquad (3.3)$$

By applying DWT, the image is actually divided i.e., decomposed into four sub-bands and critically sub sampled as shown in fig 3.1(1):



(a) One-Level (b) Two-Level

Fig 3.1(1): Image Decomposition

3.3 Denoise Procedure

Wavelets are especially well suited for studying non-stationary signals and the most successful applications of wavelets have been in compression, detection and denoising. In recent years, there has been a fair amount of research on wavelet based image denoising. The algorithm is simple but provides good results for a wide variety of signals. The method consists of applying the DWT to the original data, thresholding the detailed wavelet coefficients and inverse transforming the set of thresholded coefficients to obtain the denoised signal. This scheme is known as Visu-Shrink and is further illustrating in the block diagram of Figure 3.2.

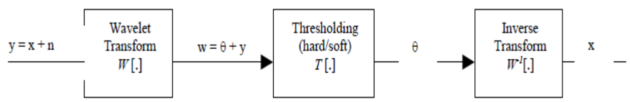


Figure 3.2: Block diagram for DWT based denoising framework

3.4 Image Denoising Filter Methods

The various filter methods for image denoising:

1) Median Filter
2) Wiener filter

Median Filter:
This filter sorts the surrounding pixels value in the window to an orderly set and replaces the center pixel within the define window with the middle value in the set.

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{g(s,t)\}$$

Wiener Filter:
Wiener2 low pass-filters an intensity image that has been degraded by constant power additive noise. Wiener2 uses a pixel wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel.
J = wiener2 (I, [m n], noise) filters the image I using pixel wise adaptive Wiener filtering, using neighborhoods of size m-by-n to estimate the local image mean and standard deviation. If you omit the [m n] argument, m and n default to 3. The additive noise (Gaussian white noise) power is assumed to be noise.

[J, noise] = wiener2 (I, [m n]) also estimates the additive noise power before doing the filtering. Wiener2 returns this estimate in noise.

3.5 Discrete Algorithm
In this work, the algorithm via the wavelet shrinkage technique is as follows:

1. Take a given original image.
2. Take the logarithmic transform of speckled image.

I. Perform multiscale decomposition of the log transformed image using wavelet transform.
II. Estimate the noise variance d using the below formula[2]

$$\hat{\sigma}^2 = \left[\frac{median(|Y_{ij}|)}{0.6745}\right]^2, \qquad Y_{ij} \in \text{Subband } HH_1$$

III. For each level in sub bands, compute the scale parameter K using the below formula.[2]

$$K = \sqrt{\log(L_k)}$$

IV. For each subband (except the lowpass residual).Compute the standard deviation **σx** using the below formula.[2]

$$\hat{\sigma}_x = \sqrt{\max(\hat{\sigma}_y^2 - \hat{\sigma}^2,\ 0)}$$

V. Compute threshold TN using below formula[2]

$$T_N = K\frac{\sigma^2}{\sigma_x}$$

if' subband variance **U:** is greater than noise variance, otherwise set TN to maximum coefficient of the sub band.
VI. Apply soft thresholding to the noisy coefficients.
VII. Invert the multiscale decomposition to reconstruct the denoised image **f** ;
VIII. Take the exponential of the 'reconstructed image obtained from step 9[2].

4. PARAMETER METRICS
4.1 PSNR
A high quality image has small value of Peak Signal to Noise Ratio (PSNR).

PSNR is defined as follow:

$$\textbf{PSNR}=\left[10\log\frac{255^2}{MSE}\right].$$

2. Coefficient of Correlation (CoC)

$$\text{CoC}= \frac{\varepsilon(g-\bar{g}).(\hat{g}-\bar{\hat{g}})}{\sqrt{\varepsilon(\Delta g-\overline{\Delta g})^2.\varepsilon(\Delta g-\overline{\Delta \hat{g}})}}$$

Where $\bar{g}$ is mean of original image, $\bar{\hat{g}}$ is mean of denoised image.

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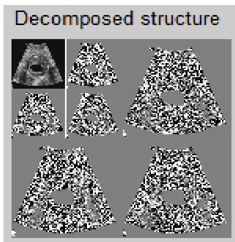
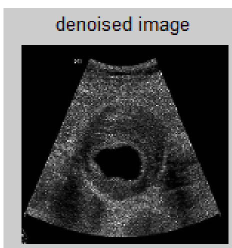
5. PERFORMANCE ANALYSIS

a) Original image

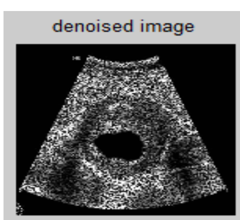
b) Noisy image



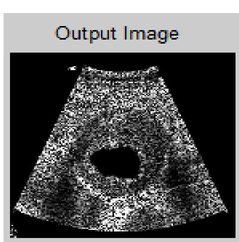
c) Decomposed structure



d) Wiener filter image



e) Median Filter image



f) Curvelet transform image

Fig 5.1(1) Images after applying filters ad curvelet transform techniques for denoising.

Table 5.1(1) PSNR results test for discrete wavelet transform (filters) and Curvelet transform on ultrasound image and σ value (1) Curvelet transform (2) wiener filter (3) media filter

Image	Curvelet transform	Wiener filter	Median filter
σ= 0.5	11.6920	21.8049	**23.5206**
σ= 1.0	11.4968	19.7270	**20.7281**
σ =1.5	12.1962	18.6646	**19.2271**
σ= 2.0	12.1746	18.0021	**18.2348**
σ =2.5	15.3100	17.5245	**17.5294**

Table 5.2(2) Coc results test for discrete wavelet transform (filters) and Curvelet transform on ultrasound image and σ value (1) Curvelet transform (2) wiener filter (3) media filter

Image	Curvelet transform	Wiener filter	Median filter
σ= 0.5	0.5485	0.8539	**0.8950**
σ= 1.0	0.5478	0.8082	**0.8297**
σ =1.5	0.5869	0.7848	**0.7852**
σ= 2.0	0.5849	**0.7732**	0.7541
σ =2.5	0.7425	**0.7632**	0.7326

6. CONCLUSION

In comparison of different filtering methods and curvelet transform method, a novel multiscale nonlinear method for speckle suppression in ultrasound images is presented. Experiments are conducted to access the better performance from denoising filtering methods. The result showed in table 5.1(1) and 5.2(2) shows that Filtering Methods of discrete wavelets transform produce better result than curvelet transform methods. Wavelet based denoising algorithms uses soft thresholding to provide smoothness and better edge preservation. Wiener filter removes noise significantly and outperforms the median filter. Despite the significance of Curvelet transform having discontinuities working over arc the wiener filter display images with more clarity.

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