A COMPARATIVE STUDY OF DIFFERENT WAVELET TECHNIQUE: DENOISING THE SPECKLE NOISE FOR ULTRASOUND IMAGES USING LABVIEW

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Abstract - Biomedical images are generally corrupted by speckle noise and Gaussian noise. Speckle noise is multiplicative type whereas other noises like Gaussian noise are additive type. It is difficult to remove multiplicative noise from images. Latest domain in the field of Image denoising and compression is using wavelet analysis. Multiresolutional image analysis using wavelets is the latest modification in the field of image enhancement and denoising. Speckle Noise is the high frequency content in the ultrasound images and can be easily removed using wavelet based thresholding technique. This paper presents study of various techniques for removal of speckle noise from images, used in biomedical applications, such as Spatial and frequency domain filter and a modified algorithm for speckle noise reduction using wavelet based multiresolutional analysis and thresholding function has been proposed incorporating different wavelets such as Haar, Coiflets, Daubechies and Symlets.

Keywords — Speckle Noise, noise filtering techniques, Multiresolutional, Wavelet thresholding, DWT transform, LabVIEW tools.

1. Introduction
Ultrasound method is one of the best imaging methods for soft tissue of body, because it is portable, no ionic radiation is used and it is relatively cheap, but the main disadvantage of this method is that images taken by this method has low quality of images that is in turn due to the presence of multiplicative noise. Speckle noise is multiplicative type whereas other noises like Gaussian noise are additive type. It is difficult to remove multiplicative noise from images.

In medical imaging, such as ultrasound images, image is generated with the help of ultrasonogram, but the basic problem in ultrasound images is speckle noise gets introduced in it. Speckle noise becomes a dominating factor in degrading the image visual quality and perception in many other images. Noise is introduced at all stages of image acquisition. There could be noises due to loss of proper contact or air gap between the transducer probe and body or noise could be introduced during the beam forming process and also during the signal processing stage. Even during scan conversion, there could be loss of information due to interpolation.

2. Related Study
Up to now, the major despeckling techniques can be loosely grouped in four categories: 1) spatial; 2) wavelet-based; 3) nonlocal filtering; and 4) variational;

They used Wiener filter, anisotropic diffusion filter, k distribution based adaptive filter and wavelet filter to de-speckle in medical ultrasound images. The Wiener filter can improve the image qualities well and simulated power spectrum of speckle can be applied on many situations.
The Anisotropic diffusion filter can also de-speckle well as long as we choose reasonable parameters, and it doesn’t need extra information of noise pattern. The K-distribution based adaptive filter can improve the image quality, the method is easy to implement and the statistics is easy to estimate and characterize. The wavelet filter is not suitable for removing the speckle in ultrasound images [4]. The Wiener Filter [5], also called as Least Mean Square filter, is given by the following expression: $H(u,v)$ shows the degradation function and $H(u,v)^*$ shows its conjugate complex. $G(u,v)$ is the degraded image. Function $S_f(u,v)$ and $S_n(u,v)$ are power spectra of original image and the noise. Wiener Filter assumes noise and power spectra of object a priori.

- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- Sparsity - the majority of the wavelet coefficients are small in magnitude.
- Edge detection - large wavelet coefficients coincide with image edges.
- Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters.

3. Proposed Approach

Latest domain in the field of Image denoising and compression is using wavelet analysis. Multiresolutional image analysis using wavelets is the latest modification in the field of image enhancement and denoising. Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. Speckle Noise is the high frequency content in the ultrasound images and can be easily removed using wavelet based thresholding technique [4].

4. Problem Formulation

A. Medical Ultrasound Speckle Pattern

Creation of speckle pattern based the number of scatters per resolution or scatter number density. For the spatially distribution and the characteristics of the imaging system can be divided into three classes: In the first category, fully formed speckle pattern occurs when many random distributed scattering exists within the resolution cell of the imaging system. Blood cells are the example of this class. The second category of tissue scatters is no randomly distributed with long-range order [4]. The third category occurs when a spatially invariant coherent structure is present within the random scatter region like organ surfaces and blood vessels [4].

B. Speckle Noise representation

Mathematically the image noise can be represented with the help of these equations below:

$$n(x,y)=f(g(u(x,y))n_1(x,y)+n_2(x,y)\ldots$$
Here \( u(x, y) \) represents the objects (means the original image) and \( v(x, y) \) is the observed image. Here \( h(x, y; x', y') \) represents the impulse response of the image acquiring process. The term \( \eta(x, y) \) represents the additive noise which has an image dependent random components \( f[g(w)] \eta_1 \) and an image independent random component \( \eta_2 \). A different type of noise in the coherent imaging of objects is called speckle noise. Speckle noise can be modeled as

\[
V(x, y) = u(x, y) s(x, y) + n(x, y) \quad (4)
\]

Where the speckle noise intensity is given by \( s(x, y) \) and \( \eta(x, y) \) is a white Gaussian noise \([1]-[3]\). The main objective of image-de-noising techniques is to remove such noises while retaining as much as possible the important signal features. One of its main shortcomings is the poor quality of images, which are affected by speckle noise.

The existence of speckle is unattractive since it disgraces image quality and affects the tasks of individual interpretation and diagnosis. Recently there have been many challenges to reduce the speckle noise using wavelet transform as a multi-resolution image-processing tool. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. The availability of an accurate and reliable model of speckle noise formation is a prerequisite for development of a valuable de-speckling algorithm.

In ultrasound imaging, however, the unified definition of such a model still remains arguable. Yet, there exist a number of possible formulae whose probability was verified via their practical use. A possible generalized model of the speckle imaging is

\[
g(n, m) = f(n, m) u(n, m) + \xi(n, m) \quad (5)
\]

Where \( g, f, u \) and \( \xi \) stand for the observed image, original image, multiplicative component and additive component of the speckle noise basically. Here \((n, m)\) denotes the axial and lateral indices of the image samples or, alternatively, the angular and range indices for B-scan images. When applied to ultrasound images, only the multiplicative component of the noise is to be considered; and thus, the model can be considerably simplified by disregarding the additive term, so that the simplified version of \((5)\) becomes,

\[
g(n, m) = f(n, m) u(n, m) \quad (6)
\]

Denoting the logarithms of \( g, f \) and \( u \) by \( gl, fl, \) and \( ul \), respectively, the measurement model becomes

\[
g l(n, m) = f l(n, m) u l(n, m) \quad (7)
\]

At this stage, the problem of de-speckling is reduced to the problem of rejecting an additive noise, and a variety of noise-suppression techniques could be evoked in order to perform this task \([1]-[12]\).

### C. Discrete Wavelet Transform

Unlike the discrete Fourier transform (DFT), which is a discrete version of the Fourier transform, the discrete wavelet transform (DWT) is not really a discrete version of the continuous wavelet transform (CWT). Instead, the DWT is functionally different from the CWT. To implement the DWT, you use discrete filter banks to compute discrete wavelet
coefficients. Two-channel perfect reconstruction (PR) filter banks are a common and efficient way to implement the DWT. The following figure shows a typical two-channel PR filter bank system.

![Fig. Two-channel PR filter bank system](image)

The signal $X(z)$ first is filtered by a filter bank consisting of $G_0(z)$ and $G_1(z)$. The outputs of $G_0(z)$ and $G_1(z)$ then are downsampled by a factor of 2. After some processing, the modified signals are upsampled by a factor of 2 and filtered by another filter bank consisting of $H_0(z)$ and $H_1(z)$.

If no processing takes place between the two filter banks, the sum of outputs of $H_0(z)$ and $H_1(z)$ is identical to the original signal $X(z)$, except for the time delay. This system is a two-channel PR filter bank, where $G_0(z)$ and $G_1(z)$ form an analysis filter bank, and $H_0(z)$ and $H_1(z)$ form a synthesis filter bank. Traditionally, $G_0(z)$ and $H_0(z)$ are low pass filters, and $G_1(z)$ and $H_1(z)$ are high pass filters. The subscripts 0 and 1 represent low pass and high pass filters, respectively. The operation ↓2 denotes a decimation of the signal by a factor of two. Applying decimation factors to the signal ensures that the number of output samples of the two low pass filters equal the number of original input samples $X(z)$. Therefore, no redundant information is added during the decomposition.

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [4]. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function $\psi$) and one for the low frequencies or smooth parts of an image (scaling function $\varnothing$). The Discrete wavelet transform (DWT) has gained wide popularity due to its excellent decorrelation property, many modern image and video compression systems embody the DWT as the transform stage. It is widely recognized that the 9/7 filters are among the best filters for DWT-based image compression. In fact, the JPEG2000 image coding standard employs the 9/7 filters as the default wavelet filters for lossy compression and 5/3 filters for lossless compression. The performance of a hardware implementation of the 9/7 filter bank (FB) depends on the accuracy with which filter coefficients are represented. Lossless image compression techniques find applications in fields such as medical imaging, preservation of artwork, remote sensing etc [4]. Day-by-day Discrete Wavelet Transform (DWT) is becoming more and more popular for digital image compression. Biorthogonal (5, 3) and (9, 7) filters have been chosen to be the standard filters.
used in the JPEG2000 codec standard. Discrete wavelet transform as reported by Zervas et al., there are three basic architectures for the two-dimensional DWT: level-by-level, line-based, and block-based architectures. In implementing the 2-D DWT, a recursive algorithm based on the line based architectures is used.

The image to be transformed is stored in a 2-D array. Once all the elements in a row is obtained, the convolution is performed in that particular row [2]. The process of row-wise convolution will divide the given image into two parts with the number of rows in each part equal to half that of the image. This matrix is again subjected to a recursive line-based convolution, but this time column-wise [2]. The result will DWT coefficients corresponding to the image, with the approximation coefficient occupying the top-left quarter of the matrix, horizontal coefficients occupying the bottom-left quarter of the matrix, vertical coefficients occupying the top-right quarter of the matrix and the diagonal coefficients occupying the bottom-right quarter of the matrix[3]. Several families of wavelets that have proven to be especially useful are included in the wavelet toolbox. The details of these wavelet Families have been shown below.

D. Coiflets

Built by I. Daubechies at the request of R. Coifman. The wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1. Coiflet scaling functions also exhibit vanishing moments. In coifN, N is the number of vanishing moments for both the wavelet and scaling functions. These filters are also referred to in the literature by the number of filter taps, which is 2N.

![Coiflet Wavelet Function Waveforms](image)

E. Symlets

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family.
The properties of the two wavelet families are similar. Here are the wavelet functions psi. The symN wavelets are also known as Daubechies' least-asymmetric wavelets. The symlets are more symmetric than the extremal phase wavelets. In symN, N is the number of vanishing moments. These filters are also referred to in the literature by the number of filter taps, which is 2N.

F. Haar Wavelets

Haar wavelet is the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1.

G. Daubechies Wavelet

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets -- thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here is the wavelet functions psi of the next nine members of the family:
H. Wavelet Domin Noise Filtering

Recently there has been significant investigations in medical imaging area using the wavelet transform as a tool for improving medical images from noisy data. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non-redundant and unique representation of the signal. Several properties of the wavelet transform, which make this representation attractive for denoising, are

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I. Multiresolution Analysis

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.
5. Wavelet Decomposition

Using the LabVIEW Wavelet Analysis Tools, you can extend the discrete wavelet transform (DWT) to 2D signal processing. The following figure shows the PR filter bank implementation of the 2D DWT, which applies the filter banks to both rows and columns of an image.

As the previous figure shows, when decomposing 2D signals with two-channel PR filter banks, you process rows first and then columns. Consequently, one 2D array splits into the following four 2D arrays:

a. low-low
b. low-high
c. high-low
d. high-high

During a two level of decomposition of an image using a scalar wavelet, the two-dimensional data is replaced with four blocks. These blocks correspond to the sub bands that represent either low pass filtering or high pass filtering in each direction. The procedure for wavelet decomposition consists of consecutive operations on rows and columns of the two-dimensional data. The wavelet transform first performs one step of the transform on all rows. This process yields a matrix where the left side contains down sampled low pass coefficients of each row, and the right side contains the high pass coefficients. Next, one step of decomposition is applied to all columns; this results in four types of coefficients, HH, HL, LH and LL.

The source image decomposes into the following four sub-images:

e. low_low—Shows an approximation of the source signal with coarse resolution.
f. low_high—Shows the details at the discontinuities along the column direction.
g. high_low—Shows the details at the discontinuities along the row direction.
h. high_high—Shows the details at the discontinuities along the diagonal direction.

You can apply the decomposition iteratively to the low-low image to create a multi-level 2D DWT, which produces an approximation of the source signal with coarse resolution. You can determine the appropriate number of decomposition levels for a signal-processing application by evaluating the quality of the decomposition at different levels. Use the Multiresolution Analysis 2D Express VI to decompose and reconstruct a 2D signal.
6. Result Analysis

The quality of an image is examined by objective evaluation as well as subjective evaluation. In subjective evaluation, the image has to be observed by a human expert. The human visual system is so complicated that it is not yet modeled properly. Therefore, in addition to objective evaluation, the image must be observed by a human expert to judge its quality.

Peak Signal To Noise Ratio

The Peak Signal to Noise Ratio (PSNR) is the ratio between maximum possible power and corrupting noise that affect representation of image. PSNR is usually expressed as decibel scale. The PSNR is commonly used as measure of quality reconstruction of image. The signal in this case is original data and the noise is the error introduced. High value of PSNR indicates the high quality of image. It is defined via the Mean Square Error (MSE) and corresponding distortion matrix, the Peak Signal to Noise Ratio [10].

\[
\text{MSE} = \frac{1}{MN} \sum \sum [f(m/n)-f'(m/n)]^2
\]

\[
\text{PSNR} = 10 \cdot \log_{10} \left( \frac{255^2}{\text{MSE}} \right) = 20 \cdot \log_{10} (255) - 10 \cdot \log_{10} (\text{MSE})
\]

Here Max is maximum pixel value of image when pixel is represented by using 8 bits per sample. This is 255 bar color image with three RGB value per pixel.
A. Sym2 wavelet output

Fig. Sym2 wavelet output images

B. DB2 wavelet output

Fig. db2 wavelet output images
C. Haar wavelet output

![Haar wavelet output Images](image1)

D. Coiflets wavelet output

![Coiflets wavelet output Images](image2)
Performance Of Noise Removal using wavelet Multiresolution

<table>
<thead>
<tr>
<th>Wavelet type</th>
<th>PSNR(db)</th>
<th>Standard Deviation</th>
<th>Correlation factor of reconstructed image</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>42.890</td>
<td>42.773</td>
<td>0.969</td>
<td>13.443</td>
</tr>
<tr>
<td>Db2</td>
<td>40.832</td>
<td>42.527</td>
<td>0.945</td>
<td>13.440</td>
</tr>
<tr>
<td>Db3</td>
<td>38.690</td>
<td>41.931</td>
<td>0.991</td>
<td>13.467</td>
</tr>
<tr>
<td>Sym2</td>
<td>40.832</td>
<td>42.527</td>
<td>0.946</td>
<td>13.440</td>
</tr>
<tr>
<td>Sym3</td>
<td>38.690</td>
<td>41.931</td>
<td>0.991</td>
<td>13.467</td>
</tr>
<tr>
<td>Coif1</td>
<td>39.121</td>
<td>42.944</td>
<td>0.982</td>
<td>13.494</td>
</tr>
</tbody>
</table>

Fig.1 PSNR value table of different wavelet types.

If the image PSNR value high means quality image will be high. so, Haar wavelet will produce the best result for denosing the speckle noise compare to other wavelets.

7. Conclusion And Future Work

In this paper, a comparative analysis is done for the different wavelet techniques for denoising and this technique follows a quantization approach that divides the input image in 4 filter coefficients and then performs further quantization on the lower order filter or higher order filter. LABVIEW software is used to implement the design. Discrete wavelet transform will be applied to construct the detail and approximation coefficients and after multilevel decomposition and filtering, reconstruction image will be created using reconstruction coefficients. With different type of wavelet like Haar, Coiflets and Symlets are analyzed for denoising the speckle noise in ultrasound images. In future, work can be done to implement this algorithm of multiresolutional analysis presented in this thesis on other types of medical imaging like CT Scan, MRI and EEG images under various different kinds of noise like speckle noise, gaussian noise, etc.

References


[6]. Wensen Feng, Hong Lei, and Yang Gao, Speckle Reduction via Higher Order Total Variation Approach, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 23, NO. 4, APRIL 2014.


[8]. Nishtha Attlas, Dr. Sheifali Gupta, Wavelet Based Techniques for Speckle Noise Reduction in Ultrasound Images: Nishtha Attlas et al Int. Journal of Engineering

