ABSTRACT

Medical images, acquired with low exposure to radiation or after administering low-dose of imaging agents, often suffer due to noise arising from physiological sources and from acquisition hardware. The main disadvantage of medical ultrasonography is the poor quality of images, which are affected by multiplicative speckle noise. The objective of the paper is to investigate the proper selection of wavelet filters and thresholding schemes which yields optimal visual enhancement of ultrasound images. To achieve this, we make use of the wavelet transform and apply multiresolution analysis to localize an image into different frequency components or useful subbands and then effectively reduce the speckle in the subbands according to the local statistics within the bands. The main advantage of the wavelet transform is that the image fidelity after reconstruction is visually lossless.

Keywords: Fidelity, Multiresolution, Speckle noise, Thresholding, Wavelet.

1. INTRODUCTION

Medical images are often deteriorated by noise due to various sources of interference and other phenomena that affect the measurement processes in imaging and data acquisition systems[1]. The small differences that may exist between normal and abnormal tissues are confounded by noise and artifacts, often making direct analysis of the acquired images difficult. As a result, improvement in the quality of medical images has been one of the central tasks for correct diagnosis as well for computation of quantitative functional information. Conventional noise filtering techniques such as median filtering and homomorphic Wiener filtering often blur the edges (Mateoa & Caballero, 2009). But preserving edge information is of prime importance to distinguish between normal and pathogenic condition. Hence, single-scale representations of signals, either in time or in frequency, are often inadequate when attempting to separate signals from noisy data. Recently, wavelet and multiscale based methods, due to their excellent localization property, have rapidly become very popular for image denoising (Unser, Aldroubi, & Laine, 2003). However, most of the wavelet thresholding methods suffer from the drawback that the chosen threshold may not match the specific distribution of signal and noise components in different scales. To address this problem, adaptive thresholding based on statistical priors of the noise models is applied to medical images of different modalities (Gupta, Kaura, Chauhan, & Saxena, 2007, 2009). But, success of these methods depends upon the accuracy of the noise models employed.

Unfortunately, medical images of different modalities, sometimes even images of same modality, suffer from different types of noise. For example, ultrasound images are affected by speckle noise and the morphological magnitude Magnetic Resonance (MR) images are corrupted by rician noise.

The rapid development of medical imaging technology and the introduction of new imaging modalities, such as endoscopy, etc., call for new image processing methods including specialized noise filtering, enhancement, classification and segmentation techniques[2]. In case of ultrasound imaging, the major shortcoming is the presence of speckle noise. Speckle is a random interference pattern present in all images obtained using coherent radiation in a medium containing subresolution scatterers. Speckle has a negative impact on ultrasound images because the speckle pattern does not correspond to the underlying organ structure in the image. Speckle occurs especially in images of the liver and kidney whose underlying structures are too small to be resolved by large wavelength ultrasound. Speckle is ultimately responsible for the poorer effective resolution of an ultrasound image when compared to other medical imaging modalities.

In ultrasound images, the noise content are multiplicative and nongaussian. Such noise is generally more
difficult to remove than additive noise, because the intensity of the noise varies with the image intensity. A model of multiplicative noise is given by

\[ y(i,j) = x(i,j)n(i,j) \]  (1)

where the speckle image \( y(i, j) \) is the product of the original image \( x(i, j) \), and the non-gaussian noise \( n(i, j) \). The indices \( i, j \) represent the spatial position over the image. In most applications involving multiplicative noise, the noise content is assumed to be stationary with unitary mean and unknown noise variance \( \sigma^2 \). To obtain an additive noise model as given in Eq. (2), we have to apply a logarithmic transformation on the speckle image \( y(i, j) \). The noise component \( n(i, j) \) is then approximated as an additive zero mean gaussian process.

\[ \ln y(i,j) = \ln x(i,j) + \ln n(i,j) \]  (2)

The DWT (Discrete Wavelet Transform) is then applied to \( \ln y(i, j) \). After applying the Inverse DWT (IDWT), the processed image is subjected to an exponential transformation to reverse the logarithmic operation. In the present paper, our objective is to investigate the effects of different wavelet filters in order to find the optimal wavelet filter and filter level[3]. Also, we evaluate the performance of different thresholding functions and shrinkage rules in order to find an optimal thresholding technique with reference to despeckling of a medical ultrasound image.

2. PROPOSED METHOD

The noise commonly manifests itself as fine grained structure in an image. The DWT provides the scale based decomposition. The DWT of an image translates the image content into an approximation subband and a set of detail subbands at different orientations and resolution scales. Typically, the bandpass content at each scale is divided into three orientation subbands characterized by Horizontal (H), Vertical (V) and Diagonal (D) directions[4]. The approximation subband consists of the so-called scaling coefficients and the detail subbands are composed of the wavelet coefficients. Here, we consider a nondecimated wavelet transform, where the number of the wavelet coefficients is equal at each scale. Thus, most of the noise tends to be represented by wavelet coefficients at the finer scales.

Discarding these coefficients would result in a natural filtering of the noise on the basis of the scale. Because the coefficients at such scales also tend to be the primary carrier of the edge information, this method sets the DWT coefficients to zero if their values are below a threshold, which is calculated using shrinkage rule. These coefficients are mostly those corresponding to noise. The edge relating coefficients on the other hand, are usually above the threshold. The IDWT of the thresholded image is the denoised image. The analysis of the results is done using statistical measures such as Variance, Mean Square Error (MSE), Signal to Noise Ratio (SNR), Peak SNR (PSNR). The experimental results show that the proposed scheme performs better than the common speckle filters in terms of these statistical measures.

3. WAVELET TRANSFORM

Wavelet Transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales. 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 \( \phi \)). High frequencies are transformed with short functions (low scale). The result of WT is a set of wavelet coefficients, which measure the contribution of the wavelets at different locations and scales. The WT performs multiresolution image analysis. The result of multiresolution analysis is simultaneous image representation on different resolution (and quality) levels.

The scaling function for multiresolution approximation can be obtained as the solution to a two scale dilatational equation

\[ \phi(x) = \sum_{k} a_{L}(k) \phi(2x - k) \]  (3)

for some suitable sequence of coefficients \( a_{L}(k) \). Once \( \phi \) has been found, an associated mother wavelet is given by a similar looking formula

\[ \psi(x) = \sum_{k} a_{H}(k) \phi(2x - k) \]  (4)

Wavelet analysis leads to perfect reconstruction filter banks using the coefficient sequences \( a_{L}(k) \) and \( a_{H}(k) \). The input sequence \( x \) is convolved with Highpass Filter (HPF) and Lowpass Filter (LPF) filters \( a_{H}(k) \) and \( a_{L}(k) \) and each result is downsampled by two, yielding the transform signals \( x_{H} \) and \( x_{L} \).

The signal is reconstructed through upsampling and convolution with high and low synthesis filters \( s_{H}(k) \) and \( s_{L}(k) \). By cascading the analysis filter bank with itself a number of times, digital signal decomposition with dyadic frequency scaling known as DWT can be formed[5]. The DWT for an image as a 2-D signal can be derived from 1-D DWT.
The easiest way for obtaining scaling and wavelet functions for two dimensions is by multiplying two 1-D functions. The scaling function for 2-D DWT can be obtained by multiplying two 1-D scaling functions:

$$\psi(x, y) = \psi(x)\psi(y) \quad (5)$$

representing the approximation subband image (LL). The analysis filter bank for a single level 2-D DWT structure produces three detailed subband images (HL, LH, HH) corresponding to three different directional orientations (Horizontal, Vertical and Diagonal) and a lower resolution subband image LL. The filter bank structure can be iterated in a similar manner on the LL channel to provide multilevel decomposition. The separable wavelets are also viewed as tensor products of onedimensional wavelets and scaling functions. If $\psi(x)$ is the onedimensional wavelet associated with onedimensional scaling function $\phi(x)$, then three 2-D wavelets associated with three subbands, called as Vertical (V), Horizontal (H) and Diagonal (D) details, are given by

$$\psi^V(x, y) = \psi(x)\psi(y) \quad (6)$$

$$\psi^H(x, y) = \psi(x)\psi(y) \quad (7)$$

$$\psi^D(x, y) = \psi(x)\psi(y) \quad (8)$$

which correspond to the three subbands LH, HL and HH, respectively.

### 3.1. Filter Order and Filter Length

The filter length is determined by filter order, but relationship between filter order and filter length is different for different wavelet families[6]. For example, the filter length is $L = 2N$ for the DW family and $L = 6N$ for the CW family, where $N$ = number of filter coefficients. HW is the special case of DW with $N = 1$ (DW1) and $L = 2$. Filter lengths are approximately, $L = \max(2N_d, 2N_r) + 2$, but effective lengths are different for LPF and HPF used for decomposition ($N_d$) and reconstruction ($N_r$) and should be determined for each filter type. Different filters have different coefficients.

Filter with a high order can be designed to have good frequency localization, which increases the energy compaction. Wavelet smoothness also increases with its order. Filters with lower order have a better time localization and preserve important edge information. Wavelet based image compression prefers smooth functions (that can be achieved using long filters) but complexity of calculating DWT increases by increasing the filter length. Therefore, in image compression application, we have to find balance between filter length, degree of smoothness, and computational complexity[7]. Within each wavelet family, we can find wavelet function that represents optimal solution related to filter length and degree of smoothness, but this solution depends on image content.

### 3.2. Number of Decompositions

The quality of denoised image depends on the number of decompositions. The number of decompositions determines the resolution of the lowest level in wavelet domain. If we use larger number of decompositions, we will be more successful in resolving important DWT coefficients from less important coefficients[8]. The Human Visual System (HVS) is less sensitive to removal of smaller details. The larger number of decomposition causes loss of the coding algorithm efficiency. The adaptive decomposition is required to achieve balance between image quality and computational complexity. Hence, the optimal number of decompositions, which depends on filter order, needs to be determined.

### 4. THRESHOLDING TECHNIQUE

There are two approaches to perform the thresholding after computation of the wavelet coefficients, namely, subband thresholding and global thresholding. In subband thresholding, we compute the noise variance of the horizontal, vertical and diagonal subbands of each decomposition level, starting from the outer spectral bands and moving towards inner spectral bands (decomposition from higher levels towards lower levels) and calculate threshold value using Bayes shrinkage or universal shrinkage rule. In global thresholding, we determine the threshold value from only the diagonal band but we apply this threshold to the horizontal, vertical and diagonal sub bands. This approach assumes, that diagonal band contains most of the high frequencies components, hence the noise content in diagonal band should be higher than the other bands. Thresholding at the coarsest level is not done because it contains the approximation coefficients that represent the translated and scaled down version of the original image. Thresholding at this level will cause the reconstruction image to be distorted.

#### 4.1. Shrinkage Scheme

The thresholding approach is to shrink the detailed coefficients (high frequency components) whose amplitudes are smaller than a certain statistical threshold value to zero while retaining the smoother detailed coefficients to reconstruct the ideal image without much loss in its details. This process is sometimes called wavelet shrinkage, since the detailed coefficients are shrunk towards zero[9]. There are
three schemes to shrink the wavelet coefficients, namely, the keep or kill hard thresholding, shrink or kill soft thresholding introduced by Donoho and the recent semi soft or firm thresholding. Shrinking of the wavelet coefficient is most efficient if the coefficients are sparse, that is, the majority of the coefficients are zero and a minority of coefficients with greater magnitude that can represent the image. The criterion of each scheme is described as follows.

Given that \( \lambda \) denotes the threshold limit, \( X_w \) denotes the input wavelet coefficients and \( Y_t \) denotes the output wavelet coefficients after thresholding, we define the following thresholding functions:

(i)Hard Thresholding:

\[
Y_T = T_{hard}(X_{w})
\]

\[
\begin{cases} 
X_{w} & \text{where } |X_{w}| \geq \lambda \\
0 & \text{where } |X_{w}| < \lambda 
\end{cases}
\]

(ii) Soft Thresholding:

\[
Y_T = T_{soft}(X_{w})
\]

\[
\begin{cases} 
\text{sgn}(X_{w}) \frac{|X_{w}| - \lambda}{2} & \text{where } |X_{w}| \geq \lambda \\
0 & \text{where } |X_{w}| < \lambda 
\end{cases}
\]

(iii) Semi-Soft Thresholding:

\[
Y_T = T_{semi-soft}(X_{w})
\]

\[
\begin{cases} 
0, & \text{where } |X_{w}| \leq \lambda \\
\text{sgn}(X_{w}) \frac{|X_{w}| - \lambda}{2}, & \text{where } \lambda < |X_{w}| \leq 2\lambda \\
\text{sgn}(X_{w}) \lambda, & \text{where } |X_{w}| > 2\lambda 
\end{cases}
\]

where \( \lambda_1 = 2\lambda \).

The hard thresholding procedure removes the noise by thresholding only the wavelet coefficients of the detailed sub bands, while keeping the lowresolution coefficients unaltered. The soft thresholding scheme shown above is an extension of the hard thresholding[10]. It avoids discontinuities and is, therefore, more stable than hard thresholding. In practice, soft thresholding is more popular than hard thresholding, because it reduces the abrupt sharp changes that occurs in hard thresholding and provides more visually pleasant recovered images. The aim of semisoft threshold 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 \( \lambda \).

4.2. Shrinkage Rule

A very large threshold \( \lambda \) will shrink almost all the coefficients to zero and may result in over smoothing the image, while a small value of \( \lambda \) will lead to the sharp edges with details being retained but may fail to suppress the speckle. We use the shrinkage rules, namely, the universal shrinkage rule and Bayes shrinkage for thresholding.

(i) Universal shrinkage rule:

An approach introduced by Donoho to denoise in the wavelet domain is known as universal thresholding as given in Eq. (12). The idea is to obtain each threshold \( \lambda_i \) to be proportional to the square root of the local noise variance \( \sigma^2 \) in each subband of a speckle image after decomposition[11]. If \( M \) is the block size in the wavelet domain,

\[
\lambda = c_1 \sqrt{\text{log}(M)}
\]

The estimated local noise variance, \( \sigma^2 \), in each subband is obtained by averaging the squares of the empirical wavelet coefficients at the highest resolution scale as

\[
\sigma^2 = \frac{1}{N} \sum_{i=0}^{N-1} |X_i|^2
\]

The threshold of Eq. (14) is based on the fact that, for a zero mean independent identically distributed (i.i.d.) Gaussian process with variance \( \sigma^2 \), there is a high probability that a sample value of this process will not exceed \( \lambda \). Thus, the universal threshold is applicable to applications with white Gaussian noise and in which most of the coefficients are zero.

(ii) Bayes shrinkage rule:

This shrinkage rule uses a Bayesian mathematical framework for images to derive subband dependent thresholds[12]. The formula for the threshold on a given subband \( s \) for the model, with zero mean variable \( X \), is given by

\[
\lambda_s = \frac{\sigma^2_s}{\sigma_{ns}}
\]

where \( \sigma_{ns} \), the estimated noise variance found as the median of the absolute deviation of the diagonal detail coefficients on the finest level (sub band HH1), is given by

\[
\sigma_{ns} = \frac{\text{median}(|X_{s}|)}{\text{median}(|X_{s}|)}
\]
\( \sigma_s \), the estimated signal variance on the subband considered, is given by

\[
\sigma_s = \sqrt{\text{Max}(\sigma_n^2 - \sigma_x^2, 0)}
\]  \hspace{1cm} (16)

and, an estimate of the variance of the observations, is given by

\[
\sigma_n^2 = \frac{1}{N_s} \sum_{k=1}^{N_s} W_k^2
\]  \hspace{1cm} (17)

in which \( N_s \) is the number of the wavelet coefficients \( W_k \) on the subband considered. In the Eq. (15), the value 0.67452 is the median absolute deviation of normal distribution with zero mean and unit variance[13]. When \((\sigma_s/\sigma_n) << 1\), the signal is much stronger than the noise. The normalized threshold is chosen to be small in order to preserve most of the signal and remove the noise. When \((\sigma_s/\sigma_n) >> 1\), the noise dominates the signal. The normalized threshold is chosen to be large to remove the noise more aggressively.

5. EXPERIMENTAL RESULTS AND DISCUSSION

A total of 3 ultrasound images are taken for the experiment. The images are spleen, kidney and liver. The images are obtained with the transducer frequency of 5-10 MHz in JPEG format.

INPUT SAMPLE 1:

ORIGINAL IMAGE

NOISY IMAGE

DENOISED IMAGE

Figure: 5.1 Simulation result of Spleen image

INPUT SAMPLE 2:

ORIGINAL IMAGE

NOISY IMAGE

DENOISED IMAGE

Figure: 5.2 Simulation result of Liver image

INPUT SAMPLE 3:

ORIGINAL IMAGE

NOISY IMAGE

DENOISED IMAGE

Figure: 5.3 Simulation result of Kidney image
5.1. Performance Comparison:

<table>
<thead>
<tr>
<th>WAVELET FILTERS</th>
<th>SNR</th>
<th>MSE</th>
<th>RMSE</th>
<th>PSNR</th>
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<td>0.04</td>
<td>77.1594</td>
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<tr>
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<td>0.0010</td>
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<td>RBIO</td>
<td>42.8068</td>
<td>0.0013</td>
<td>0.0364</td>
<td>76.9</td>
</tr>
</tbody>
</table>

6. CONCLUSION

In this paper, a wavelet based method for denoising medical ultrasound images is proposed. The experimentation is carried out on ultrasound images of spleen, liver and kidney. The results show that wavelet transforms can denoise the speckle images more effectively. The performance evaluation of the proposed method is done in terms of Variance, MSE, RMSE, PSNR and SNR values computed from the despeckled image. It is observed that subband threshold function, using Bayes shrinkage rule and soft thresholding technique, gives superior results than other thresholding techniques.

REFERENCES


