A Novel Threshold Technique for Eliminating Speckle Noise In Ultrasound Images

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Abstract. Ultrasound images are degraded as they contain speckle noise. Recently image denoising using the wavelet transform has been attracting much attention. The work in this paper includes different filtration techniques (Wiener and Median) and a proposed novel technique that extends the existing technique by improving the threshold function parameter K which produces results that are based on different noise levels. A signal to mean square error as a measure of the quality of denoising was preferred.

Keywords: Adaptive Threshold, Bayes Shrink, Denoising, Wavelet Transform, Ultrasound Images.

Introduction

Ultrasound is a powerful technique for imaging the internal anatomy (e.g., abdomen, breast, liver, kidney, and musculoskeletal). It is relatively inexpensive, noninvasive, harmless for the human body, and portable, but it suffers from a main disadvantage, i.e., contamination by speckle noise. Speckle noise significantly degrades the image quality and complicates diagnostic decisions for discriminating fine details in ultrasound images. Many techniques have been proposed to reduce this noise [2]–[10]. Early methods use various spatial filters such as average, median, and Wiener filter [2]–[6]; however, they usually do not accurately preserve all the useful information such as anatomical boundaries in the image. Recently, wavelet-based despeckling has been considered [7]–[11]. These methods usually include: 1) noisy image; 2) wavelet transformation; 3) modification of noisy coefficients using shrinkage function; and 4) inverse wavelet transformation; The first step is exerted to convert the multiplicative speckle noise into an additive noise [6], [7], and, after that, a wavelet-shrinkage technique s [12]–[20] is employed for noise reduction. Wavelet-based image denoising methods are formulated as a Bayesian estimation problem. Thus, the employed probability density function (pdf) for noise-free data and noise (for wavelet coefficients of log-transformed data), and the type of estimator have significant impact on the performance of the noise reduction process. The preliminary classification step in the proposed method relies on the persistence of useful wavelet coefficients across the scales [23], and is related to the one in [24], but avoids its iterative procedure. In contrast to [24], and related methods like [21], [22], where the inter-scale correlations between wavelet coefficients are used for a “hard” selection of the coefficients from which the denoised image is reconstructed, our algorithm performs a soft modification of the coefficients adapted to the spatial image context. The classification step of the proposed method involves an adjustable parameter that is related to the notion of the expert-defined “relevant image features”. In certain applications the optimal value of this parameter can be selected as the one that maximizes the signal-to-noise ratio (SNR) and the algorithm can operate as fully automatic. However, we believe that in most medical applications the tuning of this parameter leading to a gradual noise suppression may be advantageous. The proposed algorithm is simple to implement and fast. We demonstrate its usefulness for denoising and enhancement of the ultrasound images.
Most of the wavelet thresholding methods suffer from a drawback that the chosen threshold may not match the specific distribution of signal and noise components in different scales. To address this issue, Simoncelli et al. [10] developed nonlinear estimators, based on formal Bayesian theory.

The rest of the paper is organized as follows. Section 2 explains the Wavelet Transform. The Adaptive wavelet threshold (bayes shrink) and estimation of proposed threshold by minimizing a Bayesian risk with squared error is explained in section 3. The speckle reduction algorithm is presented in section 4. Experimental results are shown in section 5 and compared with Median filter and Wiener filter.

Wavelet Transform

The DWT is identical to a hierarchical subband system where the subbands are logarithmically spaced in frequency and represent octave-band decomposition. Due to the decomposition of an image using the DWT [25] the original image is transformed into four pieces which is normally labeled as LL, LH, HL and HH as in the schematic depicted in Fig. 1 a. The LL subband can be further decomposed into four subbands labeled as LL2, LH2, HL2 and HH2 as shown in Fig. 1 b.

![Wavelet Transform Diagram](image)

Fig. 1 Image decomposition by using DWT

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

- **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 subband tend to form spatially connected clusters

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.

Adaptive Wavelet Threshold

**Bayes Shrink.** Wavelet shrinkage is a method of removing noise from images in wavelet shrinkage, an image is subjected to the wavelet transform, the wavelet coefficients are found, the components with coefficients below a threshold are replaced with zeros, and the image is then reconstructed[26]. In particular, the bayes shrink method has been attracting attention recently as an algorithm for setting different thresholds for every subband[27]. Here subbands are frequently bands that differ from each other in level and direction. The BS method is effective for images including noise.

Bayes Shrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [28]. The Bayes threshold, is defined as
\[ T_B = \frac{\sigma^2}{\sigma^s}. \]  

(1)

The observation model is expressed as follows:

\[ W = S + N \]  

(2)

Here \( W \) is the wavelet transform of the degraded image, \( S \) is the wavelet transform of the original image, and \( N \) denotes the wavelet transform of the noise components following the

\[ W(x, y) = S(x, y) + N(x, y) \]  

(3)

\[ \sigma^2_w = \sigma^2_s + \sigma^2 \]  

(4)

\( \sigma^2_w \) is computed as below:

\[ \sigma^2_w = \frac{1}{n^2} \sum_{x=1}^{n} \sum_{y=1}^{n} w^2(x, y) \]  

(5)

The variance of the signal, \( \hat{\sigma}_s \) is computed as

\[ \hat{\sigma}_s = \sqrt{\max(\sigma^2_y - \sigma^2, 0)} \]  

(6)

With this we can compute the bayes threshold.

**Proposed Bayes Shrink.** There is the problem of noise not being sufficiently removed in an image processed using bayes shrink method[1]. But proposed bayes shrink can remove noise better than bayes shrink. It performs its processing using threshold values that are different for each subband coefficient the threshold \( T \) can be determined as follows:

\[ K = J \times \frac{\sqrt{\log(L_k)}}{m} \]  

(7)

Where \( L_k \) is the length of band with total number of decomposition \( J \) and \( m \) is mean.

\[ T_B = K \frac{\sigma^2}{\sigma_s} \]  

(8)

Where the noise variance \( \sigma^2 \) is estimated from subband HHI, using the formula [28][27]

\[ \hat{\sigma}^2 = \left( \frac{\text{median}(|Y_{ij}|)}{0.6745} \right)^2 \quad Y_{ij} \in \text{Subband HH1} \]  

(9)

and the standard deviation \( \hat{\sigma}_x \) of the subband is computed by

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

(10)

when \( \sigma_x^2 \geq \sigma_y \) & \( \sigma_x \) is taken to be zero i.e. threshold is infinity or in practice it is taken as maximal value f subband, setting all the coefficients to zero. Since \( Y \) is modeled as zero mean \( \sigma_y \) is computed as
\[ \sigma_y = \sqrt{\frac{1}{h^2} \sum_{i,j=1}^{n^2} y_{ij}^2} \]  

(11)

where \( n \times n \) is size of subband.

**Algorithm For Denoising bases on new threshold.**

We can summarize the process Bayes Shrink, proposed bayes shrink as follows:

**A.** Input Noisy ultrasound image.

**B.** Perform Multiscale decomposition of the image corrupted by Speckle noise using wavelet transform.

**C.** Estimate the noise variance \( \sigma^2 \) using equation (9).

**D.** For each scale compute the scale parameter \( K \).

**E.** from equation (7)

**F.** For each subband (except the lowpass residual).

- Compute the standard deviation \( \sigma_x \) using equation (10).
- Compute threshold \( T \) using equation (8) if subband variance \( \sigma^2_x \) is greater than noise variance, otherwise set \( T \) to maximum coefficient of the subband.

**G.** Invert the multiscale decomposition to reconstruct the denoised image.

**Experimental Result**

Our test consists of an ultrasound image baby, kidney, liver of size (256×256). The kind of noise is Speckle with variance 0.09,0.1,……0.3. In the test, Speckle noise is added to original image. In this test, we used from several methods for image denoising. Median filter and other nonlinear filters, as well as wiener filters and other optimization filters have been used as denoising methods for images with noise, as shown in figure 3, figure4, figure5. As well as, the wiener filter is more effective than the conventional linear filter high frequency components in images and it works efficiently when the noise is Speckle noise. The results show both of filter, denoise weakly as well as new blurriness occurs in the processed image. Therefore they remove a lot of details of original image during denoising.
In order to quantify the achieved performance improvement, three different measures were computed based on the original and the denoised data. For quantitative evaluation, an extensively used measure is the mse defined as shown in eq (12).

$$\text{mse} = \frac{1}{K} \sum_{i=1}^{K} (\hat{S}_i - S_i)^2$$

(12)

where

$S_i$: original image;

$\hat{S}_i$: denoised image;

$K$: image size.

The standard signal to noise ratio (SNR) is not adequate to evaluate the noise suppression in case of multiplicative noise. Instead, a common way to achieve this in coherent imaging is to calculate the signal-to-mse (S/mse) ratio, defined as [24,25]

$$S/\text{mse} = 10 \log_{10} \left( \frac{\sum_{i=1}^{K} S_i^2}{\sum_{i=1}^{K} (\hat{S}_i - S_i)^2} \right)$$

(13)

Remember that in ultrasound imaging, we are interested in suppressing speckle noise while at the same time preserving the edges of the original image that often constitute features of interest for diagnosis.

Thus, in addition to the above quantitative performance measures, we also consider a qualitative we used a parameter originally defined in [29] and [30]. In soft threshold, we used from one threshold value. In the wavelet decomposition, the magnitude of the coefficients varies depending on the decomposition level. Hence, if all levels are processed with one threshold value the processed image may be overly smoothed so that sufficient information preservation is not possible and the image get blurry. Therefore the method is not suitable. The result shows Proposed Bayes shrink performs denoising that is consistent with the human visual system that is less sensitive to the presence of noise in vicinity of edges. However, the presence of
noise in flat regions of the image is perceptually more noticeable by the human visual system. Bayes shrink performs little denoising in high activity sub-regions to preserve the sharpness of edges but completely denoised the flat sub-parts of the image.

The coefficient of correlation ($\rho$) is given by:

\[
\rho = \frac{r(s-\hat{s})}{\sqrt{r(s-\hat{s})(s-\hat{s})}}
\]  

(14)

The $\rho$ is the key measure of similarity between the original and the denoised image. The closer the $\rho$ is to 1, the stronger the correlation between the original and the denoised image.

Table 1. Image Performance Measure on Ultrasound baby

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>Median</th>
<th>Wiener</th>
<th>Bayes</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma=0.09$</td>
<td>S/MSE</td>
<td>15.7588</td>
<td>17.0436</td>
<td>18.9654</td>
</tr>
<tr>
<td></td>
<td>CoC</td>
<td>0.9967</td>
<td>0.9101</td>
<td>0.9937</td>
</tr>
<tr>
<td>$\sigma=0.1$</td>
<td>Median</td>
<td>Wiener</td>
<td>Bayes</td>
<td>Proposed</td>
</tr>
<tr>
<td></td>
<td>S/MSE</td>
<td>15.7377</td>
<td>17.0086</td>
<td>18.9598</td>
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<tr>
<td></td>
<td>CoC</td>
<td>0.9866</td>
<td>0.9900</td>
<td>0.9937</td>
</tr>
<tr>
<td>$\sigma=0.3$</td>
<td>Median</td>
<td>Wiener</td>
<td>Bayes</td>
<td>Proposed</td>
</tr>
<tr>
<td></td>
<td>S/MSE</td>
<td>15.1724</td>
<td>16.1086</td>
<td>17.8363</td>
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<tr>
<td></td>
<td>CoC</td>
<td>0.9847</td>
<td>0.9877</td>
<td>0.9904</td>
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</table>

Table 2. Image Performance Measure on Ultrasound kidney

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>Median</th>
<th>Wiener</th>
<th>Bayes</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma=0.09$</td>
<td>S/MSE</td>
<td>12.1007</td>
<td>13.6522</td>
<td>15.1059</td>
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<td></td>
<td>CoC</td>
<td>0.9689</td>
<td>0.9783</td>
<td>0.9846</td>
</tr>
<tr>
<td>$\sigma=0.1$</td>
<td>Median</td>
<td>Wiener</td>
<td>Bayes</td>
<td>Proposed</td>
</tr>
<tr>
<td></td>
<td>S/MSE</td>
<td>12.1001</td>
<td>13.6382</td>
<td>15.0104</td>
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<tr>
<td></td>
<td>CoC</td>
<td>0.9687</td>
<td>0.9782</td>
<td>0.9242</td>
</tr>
<tr>
<td>$\sigma=0.3$</td>
<td>Median</td>
<td>Wiener</td>
<td>Bayes</td>
<td>Proposed</td>
</tr>
<tr>
<td></td>
<td>S/MSE</td>
<td>11.6546</td>
<td>12.8754</td>
<td>13.8761</td>
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<tr>
<td></td>
<td>CoC</td>
<td>0.9653</td>
<td>0.9938</td>
<td>0.9793</td>
</tr>
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</table>

Table 3. Image Performance Measure on Ultrasound liver

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>Median</th>
<th>Wiener</th>
<th>Bayes</th>
<th>Proposed</th>
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<tbody>
<tr>
<td>$\sigma=0.09$</td>
<td>S/MSE</td>
<td>16.1193</td>
<td>17.1058</td>
<td>22.2087</td>
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<tr>
<td></td>
<td>CoC</td>
<td>0.9904</td>
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<td>0.9970</td>
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<tr>
<td>$\sigma=0.1$</td>
<td>Median</td>
<td>Wiener</td>
<td>Bayes</td>
<td>Proposed</td>
</tr>
<tr>
<td></td>
<td>S/MSE</td>
<td>17.0599</td>
<td>16.5109</td>
<td>22.9181</td>
</tr>
<tr>
<td></td>
<td>CoC</td>
<td>0.9903</td>
<td>0.9880</td>
<td>0.9968</td>
</tr>
</tbody>
</table>
The result shows all of the adaptive wavelet threshold (bayes shrink, modified bayes shrink and proposed bayes shrink) remove noise better than others as shown in table1, table2, table 3. But, it depends on noise, one of the adaptive wavelet threshold is better. Proposed bayes shrink is the best because it has maximum SNR (signal to noise ratio) and coefficient of correlation.

<table>
<thead>
<tr>
<th>$\sigma = 0.3$</th>
<th>Median</th>
<th>Wiener</th>
<th>Bayes</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoC</td>
<td>0.9868</td>
<td>0.9841</td>
<td>0.9897</td>
<td>0.9888</td>
</tr>
</tbody>
</table>

Fig. 4 Noise suppression in ultrasound kidney using the proposed method, Bayes shrink, Wiener filter, Median filter

Fig. 5 Noise suppression in ultrasound liver using the proposed method, Bayes shrink, Wiener filter, Median filter
Conclusion

The technique gives better results which vary as the noise variance increases. Our new threshold function is better as compare to other threshold function, gives a greater amount of signal to mean square error and preserves background information. In future we can use same threshold function for medical images as well as texture images to get denoised image with improved performance parameter.

References


