Comparative Analysis of various Spatial Filters for De-speckling Ultrasound Images

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Abstract: Medical ultrasound images are generally corrupted with different types of noises in its acquisition and transmission. Speckle, a type of locally interrelated multiplicative noise corrupts the medical ultrasound images which in turn makes the visual observation challenging. Speckle noise is generally considered as a key source of noise in ultrasound images and must be filtered out without disturbing the necessary characteristics of an image. In this paper, eleven speckle reducing spatial filters are implemented and compared for the removal of speckle noise in ultrasound images. Experiments are conducted on several ultrasound images that are degraded by speckle noise. Some established performance metrics such as Figure of Merit (FoM), Mean Square Error (MSE), Structural Similarity Index (SSIM), Peak Signal to Noise Ratio (PSNR), Bhattacharyya Coefficient (BC) and Method Noise are used to compare the performance of filters in terms of structure preservation, edge preservation and smoothing.

1. Introduction

Ultrasound is used to generate images of human body for over half century. Dr. Karl Theo Dussik, was the first one to apply ultrasound as a tool for medical diagnostic to image the brain. Now ultrasound is a widely used technology in medicine and other fields. It is free of the risk of radiations and is comparatively inexpensive when compared to other imaging technologies. In ultrasound imaging the images can be acquired in real time which provides instantaneous visual guidance for many procedures [25].

However the main concern in ultrasound imaging is the presence of the speckle noise in the images. Speckle noise is a multiplicative noise. The intrinsic nature of this noise leads to degradation of the contrast and resolution of the images. The speckle noise is the main factor that bounds the contrast resolution in diagnostic ultrasound imaging and in turn limits the detectability of some small wounds and the corrupted image is generally difficult for the non-specialist to understand. [2][12][6]. Although various speckle reduction techniques and filters have been introduced, enhanced and studied by the researchers, but till now there is no perfect method that can consider all the constraints such as smoothing, details and edge preservation. Thus a comparative study is definitely needed to compare filters in terms of conserving the edges, features and the efficiency of different filters. This paper is divided into some sections: In the section 2 several de-speckling filters in the spatial domain are discussed. In section 3, performance analysis metrics are discussed. Section 4 contains the results and discussions. Acknowledgement and references are given in section 5 and 6 respectively.

2. Filters for de-speckling

2.1 Lee filter

The lee filter [3], [4] is based on the (MMSE) minimum mean square error that produces a speckle free image governed by the relationship given in following equation:

\[ U(x,y) = I(x,y)W(x,y) + I_4(x,y)(1-W(x,y)) \]  

(1)

Here \( I_4 \) is the mean of the intensity within the filter window and \( W(x,y) \) is adaptive filter coefficient that is calculated as

\[ W(x,y) = 1 - \frac{C_S}{C_I + C_S} \]  

(2)

Here \( C_I \) represents the coefficient of variation of noised image whereas, \( C_S \) is the coefficient of variation of noise in the image. Generally, \( W(x,y) \) approaches to zero in areas that are uniform and it approach to 1 at edges that result in little modification of the pixel values that are near the edges [16].
2.2 Kuan filter

The kuan filter is also based on minimum mean square error for speckle reduction as given in equation:

$$U(x,y) = I(x,y)W(x,y) + I_1(x,y)(1 - W(x,y))$$

(3)

Here $I_1$ represents mean of intensity in the filter window and $W(x,y)$ denotes the coefficient of adaptive filter which can be calculated as:

$$W(x,y) = \frac{1 - C^2}{1 + C^2}$$

(4)

Here $C_i$ is the coefficient of variation of the noised image and $C^2$ is the coefficient of variation of noise in the image. Generally, $W(x,y)$ approaches to zero in areas that are uniform and it approach to unity at edges that result in little modification of the pixel values that are near the edges [16].

2.3 Frost filter

Frost filter is proposed by Frost et al [5]. This is an adaptive filter designed to de-speckle images based on local statistics similarly to Lee filter. The noisy image is modeled as:

$$f(x,y) = [g(x,y)n(x,y)] \ast h(x,y)$$

(5)

Here $f(x,y)$, $g(x,y)$ and $n(x,y)$ represents noisy image, noise free image and the noise in spatial coordinates $(x,y)$ respectively. $h(x,y)$ is system impulse response.

The noise-free image $g(x,y)$ is computed from $f(x,y)$ by using the MMSE estimator. The every pixel value is computed by using a weighted average of the pixels values of the neighborhood pixels in spatial domain. The weight $w$ is determined by the local statistics of the data.

$$w = ka e^{-2[t]}$$

(6)

Here $\propto f f \cdot k$ is a constant normalization factor and $|t|$ is spatial geometric distance between the neighborhood pixels and the center pixel [19].

2.4 Geometric de-speckle filter (Gf4d)

Geometric filtering considers speckle noise as narrow valleys and walls. Thus through iterative repetition, the geometric filter slowly tears down the narrow walls that are bright edges and fills up the row valleys that are dark edges.

The gf4d filter [9] uses a non-linear noise reduction method. This filter compares the intensity of central pixel in a 3*3 neighborhood with its eight neighbors and depending upon the neighborhood pixel intensities, the intensity of central pixel is incremented or decremented. The following steps are computed in this filter:

1) Select direction and assign pixel values:
Select a direction for instance, north-south (NTST) and the three corresponding consecutive pixels a, b, c respectively [see Fig. 1 (a) and (b)].

2) Carry out the central pixel adjustments: Do the intensity adjustments as following [see Fig. 1 (b)]:
- If $a \geq b + 2$ then, $b = b + 1$.
- If $a > b$ and $b \leq c$ then, $b = b + 1$.
- If $c > b$ and $b \leq a$ then, $b = b + 1$.
- If $c \geq b + 2$ then, $b = b + 1$.
- If $a \leq b - 2$ then, $b = b - 1$.
- If $a < b$ and $b \geq c$ then, $b = b - 1$.
- If $c < b$ and $b \geq a$ then, $b = b - 1$.
- If $c \leq b - 2$ then, $b = b - 1$.

$$(7)$$

3) Repeat: Repeat the steps 1 and 2 for west-east (WE) direction, west-north to southeast (WN to SE) direction, and then north-east to west-south direction (NE to WS) [see Fig. 1(a)].

Figure 1: (a) Directions of implementation of geometric filter gf4d, (b) Pixels selected for NTST direction (intensity of the central pixel b is adjusted according to the values of the intensities of the pixels a, b and c) [14].

2.5 Median filter and Hybrid median

The median of a certain set of numbers is the number which can partition the given set into two subsets with an equal number of elements such this number is greater than or equal to the elements in one subset and less than or equal to the number of elements in other subset. The median filter [8] is a simple nonlinear operator that replaces the central pixel of the window with the median-value of the
neighborhood pixels. The hybrid median filter increases the optical perception and also preserves the edges. This filter is therefore utilized to maintain as well as enhance the edges in ultrasound images [19].

2.6 Wiener filter

Wiener filter uses the first order statistics such as the mean and the variance of the neighborhood. This filter follows the following equation:

\[ f_{x,y} = \hat{g} + k_{x,y} \left( g_{x,y} - \hat{g} \right) \]  

Here \( f_{x,y} \) is the projected pixel value that is noise-free, \( g_{x,y} \) denotes the noisy pixel value into moving window, \( \hat{g} \) represents local mean value of the \( N_x \times N_y \) region that surrounds the \( g_{x,y} \), \( k_{x,y} \) is a weighting factor with \( k \in [0,1] \) and \( x, y \) represents the pixel coordinates. The factor \( k_{x,y} \) denotes the function of local statistics into the moving window.

2.7 Bilateral filter

Bilateral filter is a non-linear filter that depends on spatial weighted midddling and it does not smooth the edges. It uses two filters of Gaussian type that is spatial domain and intensity domain. At some component position \( m \), the output of the filter can be calculated by:

\[ I(m) = \sum_{m \in [-w, w]} \sum_{n \in [-w, w]} W(m,n) I(m,n) I(n) \]

Here \( w \) is the span of filter, that have the window size \( (2w+1) (2w+1) \). The \( W(m,n) \) component uses Euclidean distance between component at the position \( m \) and neighbor component at the position \( n \) in order to estimate the geometric closeness, whereas the \( W_I(m,n) \) component uses the absolute difference between intensity values \( I(m) \) and \( I(n) \) in order to determine the photometric similarity. The spatial and intensity domain are given by the equations as:

\[ W_s = \exp \left( -\frac{|m-n|^2}{2\sigma_s^2} \right) \]

\[ W_i = \exp \left( -\frac{|I(m)-I(n)|^2}{2\sigma_i^2} \right) \]

Here both the parameters \( \sigma_s \) and \( \sigma_i \) controls the behavior of domain. \( W_s \) decrease as the distance between the components increases [10], [17].

2.8 Kuwahara filter

This filter considers the most homogenous neighborhood around every pixel [7]. The filter operates in a \( 5 \times 5 \) pixel neighborhood. The center pixel value of \( 1 \times 5 \) neighborhood is replaced by the median gray value of \( 1 \times 5 \) mask. The user selects the number of the iterations. The Kuwahara filter is able to smooth the image as well as it preserves the edges [20].

2.9 Speckle reducing anisotropic diffusion filter (SRAD)

A diffusion based technique for speckle reduction is introduced by Yu and Acton [12]. The function of the instantaneous coefficient of variation (ICOV) \( q \), and given by ratio of the standard deviation to the mean:

\[ q(x,y,t) = \frac{std(I(x,y,t))}{\bar{I}(x,y,t)} \]

The diffusion function \( c(.) \) is given by

\[ c[q(x,y,t), q_0(t)] = \left( 1 + \frac{q^2(x,y,t) - q_0(t)}{q^2(x,y,t)[1+q^2(t)]} \right) \]

Here \( q_0 \) is the speckle scale function [20].

2.10 Non local mean filter (NLM)

Buades [13] proposed Nonlocal means (NLM) filter. In the NLM filter the intensity values of the pixels can be related to the pixel intensity of the entire image. The expression for the restored intensity of a pixel \( x_i \) is as following:

\[ NL(u)(x_i) = \sum_{x_j \in \Omega} w(x_i,x_j) u(x_j) \]

Here \( w(x_i,x_j) \) denotes the weight given to \( u(x_j) \) in order to reinstate the pixel \( x_i \). The \( w(x_i,x_j) \) estimates the similarity between \( x_i \) and \( x_j \), with the constraints such as \( w(x_i,x_j) \in [0, 1] \).
The weights are calculated as

$$w(x_i, x_j) = \frac{1}{Z_i} e^{-\frac{(\mu_i - \mu_j)^2}{2\sigma_i^2}}$$  \hspace{1cm} (17)

Here, $N_i$ and $N_j$ are the intensities of the local neighborhoods on pixels $x_i$ and $x_j$, $Z_i$ represents normalization constant and $h$ is the degree of filtering which controls the decay of the exponential function.

### 3. Performance evaluation metrics

To evaluate the performance of the various filters quantitatively, following metrics are calculated:

#### 3.1 Figure of merit (FoM)

This parameter measures the performance of filter to preserve the edges of the image.

$$\text{FoM}(I_{\text{filt}}, I_{\text{ref}}) = \frac{1}{\max(E_{\text{filt}}, E_{\text{ref}})} \sum_{i=1}^{N} \frac{1}{1 + d_i^2 \alpha}$$  \hspace{1cm} (18)

Here, $E_{\text{filt}}$ and $E_{\text{ref}}$ represents the number of the edge pixels in edge maps of the images $I_{\text{filt}}$ and $I_{\text{ref}}$. $\alpha$ is $\frac{1}{\sigma}$, $d_i$ denotes the Euclidean distance in between the ith edge pixel and some nearest ideal edge pixel of original image. The value of FoM lies between 0 and 1 where 1 represents perfect edge preservation of image [20] [16].

#### 3.2 Structural similarity (SSIM) index

SSIM is used to compare structure, contrast and luminance between the original and filtered image.

$$\text{SSIM} = \frac{1}{M} \frac{2\mu_x \mu_y + C_1}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$  \hspace{1cm} (19)

Here $\mu_x$, $\mu_y$ and $\sigma_x$, $\sigma_y$ are the means and standard deviations of the images that are compared. $\sigma_{xy}$ is the covariance between the images. $C_1$, $C_2 \ll 1$ Indicate stability. The values of SSIM lie between 0 and 1 [16][20].

#### 3.3 Peak signal to noise ratio (PSNR)

This parameter provides the quality of image in terms of powers of the original and filtered images.

$$\text{PSNR} = 10 \log_{10} \frac{(2^8 - 1)^2}{\text{MSE}} = 10 \log_{10} \frac{255^2}{\text{MSE}}$$  \hspace{1cm} (20)

Here MSE is mean square error value.

#### 3.4 Mean square error (MSE)

This parameter quantifies the amount of de-speckling between the original and filtered image.

$$\text{MSE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} \left| f_{x,y} - g_{x,y} \right|^2$$  \hspace{1cm} (21)

Where the pixel of original image is $f_{x,y}$, and $g_{x,y}$ is the filtered image pixel.

#### 3.5 Bhattacharyya coefficient

This coefficient is the measure of extent of closeness between two statistical samples or two statistical populations. It is usually used to define the relative closeness between the considered two samples.

$$BC(i,j) = \sum_{x \in X} \sqrt{p(x) \bar{p}(x)}$$  \hspace{1cm} (22)

Here BC is Bhattacharyya coefficient for two samples i(x), j(x) and n is the number of partitions [23].

#### 3.6 Method noise

Method noise is used to represents the amount of de-speckling done by the filter in the form of images. The de-speckling filter’s performance is good if there is less structural information in the method noise image and noise is present in more extent.

### 4. Results and discussions

Eleven speckle reducing spatial filters are implemented and compared for the removal of speckle noise in ultrasound images. Experiments are conducted on several ultrasound images that are degraded by speckle noise. Some established performance metrics such as Figure of Merit (FoM), Mean Square Error (MSE), Structural Similarity Index (SSIM), Peak Signal to Noise Ratio (PSNR), Bhattacharyya Coefficient (BC) and Method Noise are used to compare the performance of filters in terms of structure preservation, edge preservation and smoothing.

Images of liver, g-tract, pancreas, appendix and gallbladder are used to perform experimental analysis. Firstly, the noise-free images are degraded
with the speckle noise with the noise levels 0.01, 0.02 and 0.03 that are introduced using Matlab by the ‘imnoise’ function.

4.1 Bar graph representation of performance metrics

The comparative analysis of the eleven filters based on the performance metrics Figure of Merit (FoM), Structural Similarity Index Metrics (SSIM), Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Bhattacharyya Coefficient (BC) in the form of bar graphs is as following:

As depicted from bar graph of Figure of Merit SRAD, Frost and NLM gives higher performance in terms of preserving the edges of the image whereas Median and Kuwahara filter are not good for preserving the edges. In case of Structural Similarity Index, NLM, SRAD, Lee, Kuan and Frost gives relatively high performance in terms of maintaining the structural information of the image whereas Median and Kuwahara filter gives the lower values of this parameter and do not preserve the structural information between the original and de-noised image.

NLM gives relatively high values of Peak Signal to Noise Ratio (PSNR) of the image followed by the SRAD and Bilateral filters. On the other hand Median and Kuwahara filter gives the lower values of this parameter. In terms of Mean Square Error, Kuwahara filter gives very high values of this parameter for the image followed by the median and wiener filters. On the other hand, Lee and Kuan filter gives the lower values of this parameter. Hence Lee and Kuan filters are best for preserving the overall quality of the image.

Median filter gives very high values of Bhattacharyya Coefficient (BC) for the image. On
the other hand, Lee and Kuan filter gives the relatively lower values of this parameter. Average value of Bhattacharyya coefficient is 0.993818 with the variance ($\sigma^2$) of 0.080852.

4.2 Comparison of filters using method noise

The method noise images of the filters are as follows:

By carefully inspecting method noise images, it is depicted that Gf4d filter contain more noise and least structural details followed by SRAD and Bilateral filters. So these filters suppress speckle noise while preserving the finer details of the image. The method noise images obtained by applying other filters contain more structural details indicating significant loss of structural information during the de-noising process.

4.3 Visual quality of de-noised images using various filters

The comparison of the visual quality of an ultrasound image with different filters is shown by following figures:
4.4 Tabular representation of results

Firstly filters are compared using the values of the performance evaluation metrics then the filters are ranked according to each parameter. Finally the overall ranking of the filters is also done.

The tabular representation of results of various filters and the ranking of the filters based on the performance parameters is given in the two tables as follows:

Table 1: Comparison of performance parameters for test image at an average of the noise levels (0.01, 0.02 and 0.03)

<table>
<thead>
<tr>
<th>Filters</th>
<th>FoM</th>
<th>SSIM</th>
<th>PSNR</th>
<th>MSE</th>
<th>BC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee</td>
<td>0.8323</td>
<td>0.8369</td>
<td>24.4507</td>
<td>22.8577</td>
<td>0.98672</td>
</tr>
<tr>
<td>Kuan</td>
<td>0.8322</td>
<td>0.8372</td>
<td>24.4760</td>
<td>22.8373</td>
<td>0.98644</td>
</tr>
<tr>
<td>Frost</td>
<td>0.877</td>
<td>0.8357</td>
<td>25.4660</td>
<td>184.927</td>
<td>0.99984</td>
</tr>
<tr>
<td>Kuwahara</td>
<td>0.7158</td>
<td>0.6362</td>
<td>17.0592</td>
<td>1279.84</td>
<td>0.99995</td>
</tr>
<tr>
<td>Gf4d</td>
<td>0.7968</td>
<td>0.7776</td>
<td>27.7509</td>
<td>119.414</td>
<td>0.99952</td>
</tr>
<tr>
<td>Median</td>
<td>0.6790</td>
<td>0.6587</td>
<td>18.1256</td>
<td>100.127</td>
<td>0.99984</td>
</tr>
<tr>
<td>Hmedian</td>
<td>0.8389</td>
<td>0.8112</td>
<td>28.0485</td>
<td>106.579</td>
<td>0.99999</td>
</tr>
<tr>
<td>Wiener</td>
<td>0.8457</td>
<td>0.8040</td>
<td>21.4405</td>
<td>467.083</td>
<td>0.99990</td>
</tr>
<tr>
<td>NLM</td>
<td>0.8816</td>
<td>0.8644</td>
<td>31.1896</td>
<td>51.2840</td>
<td>0.99977</td>
</tr>
<tr>
<td>SRAD</td>
<td>0.8858</td>
<td>0.8436</td>
<td>30.3557</td>
<td>62.8662</td>
<td>0.99944</td>
</tr>
<tr>
<td>Bilateral</td>
<td>0.7916</td>
<td>0.7799</td>
<td>29.4325</td>
<td>76.8686</td>
<td>0.99911</td>
</tr>
</tbody>
</table>

Table 2: Performance evaluation and ranking of the filters

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Filters 1</th>
<th>FoM</th>
<th>SSIM</th>
<th>PSNR</th>
<th>MSE</th>
<th>BC</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee</td>
<td>6th</td>
<td>4th</td>
<td>8th</td>
<td>8th</td>
<td>10th</td>
<td>9th</td>
<td>11th</td>
</tr>
<tr>
<td>Kuan</td>
<td>7th</td>
<td>3rd</td>
<td>7th</td>
<td>7th</td>
<td>11th</td>
<td>8th</td>
<td>10th</td>
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<tr>
<td>Frost</td>
<td>3rd</td>
<td>5th</td>
<td>6th</td>
<td>6th</td>
<td>5th</td>
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<td>11th</td>
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<td>Gf4d</td>
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<td>Median</td>
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<td>10th</td>
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<td>10th</td>
<td>4th</td>
<td>11th</td>
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<td>Hmedian</td>
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<tr>
<td>Wiener</td>
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<td>9th</td>
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<tr>
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<td>1st</td>
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<tr>
<td>SRAD</td>
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<td>2nd</td>
<td>8th</td>
<td>2nd</td>
<td>1st</td>
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<tr>
<td>Bilateral</td>
<td>9th</td>
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<td>3rd</td>
<td>9th</td>
<td>7th</td>
<td>11th</td>
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</tbody>
</table>

As represented in the tables, SRAD, NLM and Frost filters gives high values of FoM, thus these filters perform better in preserving the edges of the image. In case of SSIM, the filters NLM, SRAD followed by Kuan and Lee computes good results. So these filters are best for maintaining the structural information of the image. NLM, SRAD and Bilateral filters gives higher values of PSNR parameters thus maintaining fidelity of the image which indicates the resemblance of the original and the de-noised image.
MSE measures the overall quality change of the image, thus a lower value of MSE is preferred. Lee and Kuan filters have the lowest rank for this parameter which indicates that Lee and Kuan filters preserve the overall quality of the image. Hmedian, Kuwahara and Wiener filters give high values of Bhattacharyya coefficient, so these filters maintain the co-relation or similarity between the images.

Overall NLM, SRAD, Hmedian and Frost filters performed better in all aspects of de-speckling whereas, the performance of Kuwahara and Median filters is not satisfactory.

4.5 Conclusions

Based on the visual inspection of ultrasound images and the quantitative result obtained in the study, it is observed that in terms of preserving the edges, NLM and Frost filters shows comparatively better performance. To maintain the structural similarity Lee, Kuan, NLM and SRAD filters computes better results. NLM, Bilateral, SRAD and Gf4d filters compute higher PSNR values. Images filtered using Hmedian, Wiener filter show high similarity with the original images.

5. Acknowledgement

Images used for experimentation are taken from www.ultrasoundcases.info. This site has a large number of the general ultrasound images obtained from the Hospital Gelderse Vallei in the Netherlands.

6. References


