A Comparative Study of Speckle Reduction Filters for Ultrasound Images of Poly Cystic Ovary

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Abstract: Ultrasound imaging is the most commonly used modality in medical diagnosis and it is corrupted by speckle noise, which is multiplicative in nature. Hence there is a need to reduce the speckle noise in ultrasound images for a better diagnosis. In this paper we discuss and compare the performance of various speckle reduction filters namely Median, Wiener, Gaussian, Bilateral, Guided, Anisotropic Diffusion and Non-Local Means (NLM). Evaluation of the filters is done by considering different performance metrics for image quality such as Mean Square Error (MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and determines the best suitable despeckling filter for the ultrasound images of polycystic ovary.

Index terms: Ultrasound images, Speckle noise, Filtering techniques, Image quality metrics, Polycysticovary.

1. INTRODUCTION

Medical ultrasound or ultrasonography is a non-invasive diagnostic tool used to view the images of internal parts of a human body. Ultrasound imaging uses sound waves to produce images which help to diagnose the disease. It uses a small transducer (probe) and ultrasound gel which is placed directly on the skin. High-frequency sound waves are transmitted from the probe into the human body. The transducer collects the sounds that bounce back and the computer uses the sound waves to generate an image. Unlike other modalities like X-ray, MRI, CT, ultrasound images have many advantages because of its low cost, not harmful and portability. But the only disadvantage is the ultrasound images are degraded by the speckle noise which makes the image analysis difficult and also to the diagnosis done by a physician. Hence to enhance the quality of the image, speckle reduction is very important step in pre-processing. An efficient speckle reduction filter can produce accurate results and helps in the correct diagnosis of the disease.

2. MATERIALS AND METHODS

A. Speckle noise

Speckle is a kind of granular noise that inherently exists and degrades the quality of the medical ultrasound images. Speckle is most often considered the dominant source of noise in ultrasound imaging and should be processed without affecting important features of an image. Speckle is an undesirable property of the image as it masks small differences in grey level[2]. Speckle is generally considered as a correlated multiplicative noise and can be converted to additive noise by applying a log operation. And the log-based speckle noise is an additive noise and can be approximated by a Gaussian probability density.

The mathematical representation of speckle noise model is given by[3].

\[ A(i,j) = B(i,j) \times n(i,j) \]  

(1)

Considering a 2-D image of size MxN, where A(i,j) is the noisy image, B(i,j) is the original image and n(i,j) is the noise, (i,j) represents pixel positions in the image. Applying logarithmic operation on equation (1)

\[ \ln(A(i,j)) = \ln(B(i,j)) + \ln(n(i,j)) \]  

(2)

Equation (2) can be written as

\[ x(i,j) = y(i,j) + z(i,j) \]

A polycystic ovary is an ovary which contains 12 or more follicles (cysts) of size 2–9 mm. The ovary contains many small antral (not dominant) follicles with eggs in them, the follicles do not develop and mature properly which leads to the formation of cysts in the ovaries[1]. In this paper ultrasound images, the importance of denoising those images and polycystic ovary are discussed in section 1. Section 2 describes the speckle noise, various filters proposed and the evaluation metrics. Section 3 shows the experimental results and in section 4 conclusions are drawn.
here \( z(i,j) \) is the additive noise which can be removed easily.

B. Speckle Reduction filters

In image processing speckle removal is considered the crucial step in pre-processing, as it acts an obstacle for image analysis for the operations segmentation, feature extraction and classification. The removal of this multiplicative noise from an ultrasound image is a big challenge. There are different types of filters namely linear filters, nonlinear filters, diffusion filters. Various despeckling filters which have been proposed earlier are applied on the ultrasound images. Lee filter[4], Frost filter[5], Kaun filter[6], are the filters initially designed for Synthetic Aperture Radar (SAR) images and later applied for ultrasound imaging. Some of the denoising filters are described below which are applicable for ultrasound images of polycystic ovaries.

a. Median filter

The median filter[7] is a simple nonlinear filter in which the middle value of pixel in the window is replaced with the median value of its neighbors. The pixel values are arranged according to the ascending order and the middle value is chosen as the median. The size of the neighborhood considered is \([3, 3]\) for better results.

b. Wiener filter

Wiener filter[15] is linear filter which is also known as Least Mean Square Filter. It can restore images even if they are corrupted or blurred. It reduces noise from image by comparing with the desired noiseless image. Wiener filter is based on computation of local image variance. Hence larger the local variance of the image then smoothing is done in lesser amount and if the local variance is small it performs more smoothing. Wiener filter is given by

\[
\mathbf{f}(u,v) = \frac{\mathbf{F}(u,v)^*}{\mathbf{F}(u,v)^* + \beta \mathbf{S}(u,v)^*} \mathbf{G}(u,v)
\]

where \( \mathbf{H}(u,v) \) is the degradation function and \( \mathbf{H}(u,v)^* \) is its complex conjugate. \( \mathbf{S}(u,v) \) is power spectra of original image, \( \mathbf{S}(u,v) \) is power spectra of noisy images and \( \mathbf{G}(u,v) \) is the degraded image.

c. Gaussian filter

Gaussian filter[16] is a local linear filter that smoothes the noisy image. It suppresses the noise by preserving the features of the image, but blurs the edges. Gaussian filter is given by

\[
G_x(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}
\]

where \( \sigma \) is the standard deviation of Gaussian distribution. Pixels in the centre of the kernel have higher weights than those on the periphery. Larger values of \( \sigma \) produce a blur. The kernel size must be increased with increasing \( \sigma \) to maintain the nature of the Gaussian filter. A gaussian kernel coefficient depends on the value of \( \sigma \).

d. Bilateral filter

Bilateral filter[13] smoothes the images by preserving edges, by means of a nonlinear combination of neighboring image values. It is non iterative in nature. Bilateral filter is a combination of range and domain filtering. It computes the filtering output at each pixel as the average of neighboring and similar pixels, weighted by the both spatial and intensity distance. The Bilateral filter is described as

\[
BF(x) = k^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi) c(\xi, x) s(f(\xi), f(x)) d\xi
\]

with a normalization

\[
k(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, x) s(f(\xi), f(x)) d\xi
\]

where \( f(x) \) is the input image, \( c(\xi, x) \) is the geometric closeness between the pixel and a point \( \xi \) and \( s(f(\xi), f(x)) \) is the photometric similarity between the pixels \( x \) and \( \xi \).

e. Guided filter:

Guided filter[10] is a linear edge preserving smoothing filter, which involves a guidance image \( I \), an input image \( x \), and an output image \( y \). Both \( I \) and \( x \) are identical. The output at the pixel \( i \) is expressed as weighted average:

\[
y_i = \sum_j W_{ij}(I) \times x_j
\]

where \( i \) and \( j \) are pixel indexes. The filter kernel \( W_{ij} \) is a function of the guidance image \( I \) and independent of \( x \). This filter is linear with respect to \( x \).

f. Anisotropic Diffusion

Diffusion filters suppress the speckle noise of an image by applying a partial differential equation (PDE). Anisotropic diffusion is an efficient nonlinear technique for performing contrast enhancement and noise reduction. It is used for smoothing image in a continuous region, and retains image edges without requiring any information from the image power spectrum. It can be directly applied to the images. Perona and Malik[14] proposed the following nonlinear PDE for anisotropic diffusion, known as PMAD:

\[
\frac{\partial I}{\partial t} = div(c(|\nabla I|) \nabla I)
\]

where \( \nabla \) is the gradient operator and \( div \) is the divergence operator, \( c(|\nabla I|) \) is diffusion coefficient.

\[
c(|\nabla I|) = \frac{1}{1 + (k |\nabla I|)^2}
\]

where \( k \) is an edge magnitude parameter. The PMAD method uses the gradient magnitude to detect an image edge or boundary as a step discontinuity in intensity. If \( |\nabla I| > K \), then \( c(|\nabla I|) \rightarrow 0 \) and the filter preserves the pixel. If \( |\nabla I| < K \), then \( c(|\nabla I|) \rightarrow 1 \) and anisotropic diffusion (Gaussian filtering) is achieved.

g. NonLocalMeans(NLM) filter

Non local means filter was originally introduced by A. Buadas et al. [8] for reduction of Gaussian noise. In this method the pixels in the noisy image are replaced by the weighted average of the similar pixels in the neighbourhood. Given a discrete noisy image \( f = \{ f(i) \mid i \in \mathbb{I} \} \), the denoised value of \( \text{NL}[f(i)] \) for pixel \( i \) is calculated as weighted average of all pixels in the image.

\[
\text{NL}[f(i)] = \sum_{j \in \mathcal{N}(i)} w(i, j) f(j)
\]

where the weight \( \{ w(i, j) \} \) is the similarity between the pixels \( i \) and \( j \), satisfying the conditions \( 0 \leq w(i, j) \leq 1 \) and \( \sum_j w(i, j) = 1 \). The similarity between two pixels \( i \) and \( j \) depends on the neighborhoods \( \mathcal{N}_i \) and \( \mathcal{N}_j \). The similarity is measured as the decreasing function of weighted Euclidean distance.

\[
d(i, j) = E[|f(N_i) - f(N_j)|^2]
\]

\( \alpha > 0 \) is the standard deviation of Gaussian kernel. The weights are given by

\[
w(i, j) = \frac{1}{Z(i)} e^{-\frac{d(i, j)}{2\alpha^2}}
\]

\( Z(i) = \sum_{j} e^{-\frac{d(i, j)}{2\alpha^2}} \), \( Z(i) \) is a normalization constant and \( h \) is degree of filtering.

The pixels with similar neighborhood have larger weights. Dissimilar neighborhood has lesser weights. Later improvements were done to NLM filter to remove the multiplicative noise using Bayesian formulation by introducing a new statistical distance measure to compare the patches the Pearson distance and the filter is known as OBNLM. In the Optimized Bayesian Non Local Means[12] a block wise approach is introduced to reduce the computing time. The Bayesian formulation of Non local means filter is given by

\[
\text{NL}(u)(B_i) = \frac{1}{|B_i|} \sum_{k \in B_i} p\left(u(B_{ik}) \mid u(B_i) \right) u(B_{ik})
\]

where \( p\left(u(B_{ik}) \mid u(B_i) \right) \) is the probability density function (pdf) of \( u(B_{ik}) \) conditional to \( u(B_i) \).

C. Image Quality Metrics

In order to measure the performance of the above denoising filters, the following four metrics are considered.

1. Mean Square Error(MSE):

Given an original image \( I \), with dimensions \( M \times N \), noisy image \( N \) and denoised image \( F \). The mean square error of original and filtered image is given by

\[
\text{MSE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [F(x, y) - I(x, y)]^2
\]

For identical images MSE is equal to zero otherwise maximum up to 255.

2. Signal to Noise Ratio(SNR):

SNR is a common measurement to evaluate the speckle reduction filter by computing the ratio between the original image and MSE. Higher SNR values shows that the filtering technique is better, and the denoised image quality is high.

\[
\text{SNR} = 10 \log_{10} \frac{\sigma^2}{\text{MSE}}
\]

where \( \sigma^2 = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (f(i, j) - \bar{f}) \) is an original image

3. Peak Signal to Noise Ratio(PSNR):

It is a metric used for the performance of the speckle noise reduction. It is a ratio between the maximum possible power of the signal and the noise image. The PSNR can be calculated as follows:

\[
\text{PSNR} = 10 \log_{10} \frac{255^2}{\text{MSE}} = 20 \log_{10} \frac{255}{\text{MSE}}
\]

Higher the values of PSNR, more the quality of an image.

4. Structural Similarity Index (SSIM)[9]:

This index is another metric for measuring the similarity between two images. This metric has much better consistency with the qualitative appearance of the image.

\[
\text{SSIM}(x, y) = \left( \frac{2 \mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \right) \left( \frac{2 \sigma_{xy} + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \right)
\]

where \( \mu_x, \mu_y \) are the means and \( \sigma_x, \sigma_y \) are the standard deviations of \( x_i \) and standard deviation \( \sigma_z = \left( \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu_x)^2 \right)^{\frac{1}{2}} \).

\( C_1 = (K_1 L^2) \), \( L \) is the dynamic range of pixels values.

\( \sigma_z = (K_2 L^2) \), \( K_1 \) and \( K_2 \) << 1.
III. EXPERIMENTAL RESULTS AND DISCUSSION:

In this section we discuss the experimental results obtained, which shows the efficiency of the proposed filters on the ultrasound images of polycystic ovary. For the purpose of experimentation five synthetic ultrasound images are considered. The speckle noise of variance 0.04 is introduced into the original test images. The window size of the median and wiener filters is taken as 3×3. The experiments are conducted in MATLAB, image quality metrics PSNR, SNR, MSE and SSIM are used for the evaluation of filters.

Experimental results of various filters proposed are illustrated in figure 1 to figure 5. Each figure consists of original ultrasound image of polycystic ovary, noisy image and the despeckled images obtained using proposed filtering methods.

Figure 1: Results obtained from different filters for polycystic ovary image. (a) original image 1 (b) noisy image with variance ($\sigma = 0.04$) (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

Figure 2: (a) original image 2 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

Figure 3: (a) original image 3 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

Figure 4: (a) original image 4 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

Figure 5: (a) original image 5 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter
The outcomes of the filtering techniques Median, Wiener, Gaussian, Guided, AD, Bilateral and OBNLM are compared and presented in table1 to table5. The tables consists of statistical values for the five synthetic images with their performance measures PSNR, SNR, MSE and SSIM for the proposed methods used in speckle noise removal of ultrasound images. The quantitative values in the tables prove that OBNLM filter gives better results than other filters.

Higher the values of PSNR and SNR, higher are the performances of the filters. MSE must be low which shows a high quality image as it represents the error between the images. SSIM values ranges from 0 to 1 indicating minimum and maximum similarity values, higher values indicates that the images are identical.

Table 1: Image quality metrics for the polycystic ovary image 1 using different filters.

<table>
<thead>
<tr>
<th>Filters/metris</th>
<th>PSNR</th>
<th>SNR</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>21.62</td>
<td>13.5</td>
<td>447</td>
<td>0.74</td>
</tr>
<tr>
<td>Wiener</td>
<td>25.38</td>
<td>17.46</td>
<td>188</td>
<td>0.81</td>
</tr>
<tr>
<td>Gaussian</td>
<td>24.68</td>
<td>16.7</td>
<td>221</td>
<td>0.84</td>
</tr>
<tr>
<td>Guided</td>
<td>24.24</td>
<td>16.3</td>
<td>244</td>
<td>0.80</td>
</tr>
<tr>
<td>PMAD</td>
<td>23.14</td>
<td>15.36</td>
<td>315</td>
<td>0.78</td>
</tr>
<tr>
<td>Bilateral</td>
<td>23.51</td>
<td>15.72</td>
<td>289</td>
<td>0.80</td>
</tr>
<tr>
<td>OBNLM</td>
<td>27.62</td>
<td>19.74</td>
<td>112</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Table 2: Image quality metrics for the polycystic ovary image 2 using different filters.

<table>
<thead>
<tr>
<th>Filters/metris</th>
<th>PSNR</th>
<th>SNR</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>23.15</td>
<td>12.50</td>
<td>314</td>
<td>0.59</td>
</tr>
<tr>
<td>Wiener</td>
<td>26.71</td>
<td>16.38</td>
<td>138</td>
<td>0.78</td>
</tr>
<tr>
<td>Gaussian</td>
<td>26.52</td>
<td>16.18</td>
<td>144</td>
<td>0.64</td>
</tr>
<tr>
<td>Guided</td>
<td>27.47</td>
<td>17.11</td>
<td>114</td>
<td>0.83</td>
</tr>
<tr>
<td>PMAD</td>
<td>26.64</td>
<td>16.30</td>
<td>140</td>
<td>0.87</td>
</tr>
<tr>
<td>Bilateral</td>
<td>26.69</td>
<td>16.43</td>
<td>139</td>
<td>0.74</td>
</tr>
<tr>
<td>OBNLM</td>
<td>27.58</td>
<td>17.18</td>
<td>113</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table 3: Image quality metrics for the polycystic ovary image 3 using different filters.

<table>
<thead>
<tr>
<th>Filters/metris</th>
<th>PSNR</th>
<th>SNR</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>22.87</td>
<td>11.84</td>
<td>335</td>
<td>0.70</td>
</tr>
<tr>
<td>Wiener</td>
<td>27.76</td>
<td>17.14</td>
<td>108</td>
<td>0.80</td>
</tr>
<tr>
<td>Gaussian</td>
<td>27.70</td>
<td>17.01</td>
<td>110</td>
<td>0.87</td>
</tr>
<tr>
<td>Guided</td>
<td>26.97</td>
<td>16.28</td>
<td>130</td>
<td>0.83</td>
</tr>
<tr>
<td>PMAD</td>
<td>26.28</td>
<td>15.70</td>
<td>152</td>
<td>0.84</td>
</tr>
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</table>

Table 4: Image quality metrics for the polycystic ovary image 4 using different filters.

<table>
<thead>
<tr>
<th>Filters/metris</th>
<th>PSNR</th>
<th>SNR</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>22.70</td>
<td>11.81</td>
<td>348</td>
<td>0.65</td>
</tr>
<tr>
<td>Wiener</td>
<td>25.06</td>
<td>14.57</td>
<td>202</td>
<td>0.77</td>
</tr>
<tr>
<td>Gaussian</td>
<td>26.62</td>
<td>16.17</td>
<td>141</td>
<td>0.88</td>
</tr>
<tr>
<td>Guided</td>
<td>25.69</td>
<td>15.17</td>
<td>175</td>
<td>0.81</td>
</tr>
<tr>
<td>PMAD</td>
<td>24.69</td>
<td>14.33</td>
<td>220</td>
<td>0.79</td>
</tr>
<tr>
<td>Bilateral</td>
<td>25.46</td>
<td>15.02</td>
<td>184</td>
<td>0.85</td>
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<tr>
<td>OBNLM</td>
<td>26.98</td>
<td>16.45</td>
<td>130</td>
<td>0.82</td>
</tr>
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</table>

Table 5: Image quality metrics for the polycystic ovary image 5 using different filters.

<table>
<thead>
<tr>
<th>Filters/metris</th>
<th>PSNR</th>
<th>SNR</th>
<th>MSE</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>23.22</td>
<td>12.62</td>
<td>309</td>
<td>0.70</td>
</tr>
<tr>
<td>Wiener</td>
<td>27.77</td>
<td>17.51</td>
<td>108</td>
<td>0.83</td>
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<tr>
<td>Gaussian</td>
<td>27.08</td>
<td>16.89</td>
<td>127</td>
<td>0.83</td>
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<tr>
<td>Guided</td>
<td>26.93</td>
<td>16.66</td>
<td>131</td>
<td>0.79</td>
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<tr>
<td>PMAD</td>
<td>26.25</td>
<td>16.12</td>
<td>154</td>
<td>0.79</td>
</tr>
<tr>
<td>Bilateral</td>
<td>26.44</td>
<td>16.31</td>
<td>147</td>
<td>0.82</td>
</tr>
<tr>
<td>OBNLM</td>
<td>28.69</td>
<td>18.53</td>
<td>87</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Further analysis of the quantitative results can be represented as graphs.

The evaluation of thedespeckling filters is done by the performance metrics PSNR, SNR, MSE, SSIM values by considering five ultrasound images of ovary is represented in graph1 to graph4. Graph1 shows the PSNR values, graph2 gives SNR values, similarly graphs 3 and 4 represents MSE and SSIM values respectively.

Experiments are also conducted on the 50 real ultrasound images and calculated the statistical results and the graphical analysis are drawn. The values obtained using the synthetic images and real images are almost identical for all the metrics. It shows that OBNLM filter is very efficient for the removal of speckle noise in the ultrasound images.
In this paper, seven different speckle filters (Median, Wiener, Gaussian, Guided, AD, Bilateral and OBNLM) are discussed. Experiments are conducted on 50 real ultrasound images of polycystic ovary. The experimental results have been compared and evaluated to find the efficient speckle filter by using the parameters PSNR, SNR, SSIM and MSE. It is shown that OBNLM filter outperforms other denoising filters. The numerical comparison is done using tables and visualization by the graphs. So we can conclude that OBNLM filter performs well and it is more appropriate among the proposed filters to remove the speckle noise by preserving the edges of the filtered image. In future, this work is extended to find a more efficient despeckling filter based on OBNLM for the ultrasound images of polycystic ovary.

REFERENCES


IV. CONCLUSION

After the analysis of graphs and tables for the synthetic and real ultrasound images of the polycystic ovaries the following observations are made. The quality metrics PSNR, SNR, MSE, SSIM values for the method OBNLM are more effective as compared to other filtering techniques. Except in the graph4 representing SSIM values, there is a small deviation of Gaussian filter for image2 as compared with other images. For the remaining performance measures the statistical values of the filters for the ultrasound images are nearly same.