Comparative Analysis of Speckle Noise Reducing Algorithms with Various Novelties

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ABSTRACT
This work provides the knowledge about adaptive and anisotropic diffusion techniques for speckle noise removal from various types of ultrasonic liver images. A comparative study is made based on the performance of various algorithm such as anisotropic, speckle reducing anisotropic diffusion algorithm(SRAD), Laplacian pyramid non-linear diffusion (LPND) with various filters like Gaussian, Sobel, Average, Disk, Unsharp and log. Finally a fused algorithm is developed which performs all the filtering techniques on the input image and the statistical parameters are calculated for the output images obtained from all the filters.

Key words
Speckle noise, Ultrasonic, SRAD, and LPND.

1. INTRODUCTION
Each imaging system suffers with a common problem of "Noise". Unwanted data which may reduce the contrast deteriorating the shape or size of objects in the image and blurring of edges or dilution of fine details in the image may be termed as noise.

Mathematically there are two basic models of Noise; additive and multiplicative. Additive noise is systematic in nature and can be easily modeled and hence removed or reduced easily. Whereas multiplicative noise is image dependent, complex to model and hence difficult to reduce. When multiplicative noise caused by the de-phased echoes from the scatters appears, it is called "Speckle Noise". Although it appears as noise but it contains useful information because it is due to surroundings of the target.

Speckle is the result of the diffuse scattering, which occurs when a sound wave (RF sound or Ultrasound) pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. In most cases, it is considered a contaminating factor that severely degrades image quality. Most speckle filters are developed for enhancing visualization of speckle images. Medical imaging like Ultrasound is very popular due to its low cost, least harmful to human body, real time view and small size [1] and [2]. Filter analysis has been done to select the best filter for a given image on the basis of some statistical parameters. Finally we designed the fused method which has various combinations of filters to give a better outcome.

1.1 Detailed Design

![Detailed Design Diagram]

Fig 1: Detailed design of proposed method with metrics of evaluation

2. SPECKLE NOISE IN ULTRASOUND IMAGES
An ultrasound-based diagnostic medical imaging technique used to visualize muscles and many internal organs, their size, structure and any pathological injuries with real-time tomography images. It is also used to visualize a fetus during routine and emergency prenatal care. Obstetric sonography is commonly used during pregnancy. It is one of the most widely used diagnostic tools in modern medicine. The technology is relatively inexpensive and portable, especially when compared with other imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Speckle noise affects all coherent imaging systems including medical ultrasound. Within each resolution
cell a number of elementary scatters reflect the incident wave towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that delays the interpretation of the image content.

In the medical literature, speckle noise is referred as “texture”, and may possibly contain useful diagnostic information. The desired grade of speckle smoothing preferably depends on the specialist’s knowledge and on the application. Physicians generally have a preference of the original noisy images more willingly than the smoothed versions because the filters even if they are more sophisticated can destroy some relevant image details [2]. Thus it is essential to develop noise filters which can secure the conservation of those features that are of interest to the physician.

2.1 Major Causes of Speckle Noise
Due to incorrect assumption the ultrasound pulse always travel in a straight line, to and fro from the reflecting interference. Another source of reverberations is that a small portion of the returning sound pulse may be reflected back into the tissues by the transducer surface itself, and generates a new echo at twice the depth [5]. Speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. The backscattered echoes from irresolvable random tissue in homogeneities in ultrasound imaging and from objects in Radar imaging undergo constructive and destructive interferences resulting in mottled b-scan image.

2.1.1 Need for filtering
Speckle degrades the quality of US images and thereby reducing the ability of a human observer to discriminate the fine details of diagnostic examination. This artifact introduces fine-false structures whose apparent resolution is beyond the capabilities of imaging system, reducing image contrast and masking the real boundaries of the tissue leading to the decrease in the efficiency of further image processing such as edge detection and automatic segmentation [6].

3. ANISOTROPIC DIFFUSION
In image processing and computer vision, anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Anisotropic diffusion is a generalization of this diffusion process it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image. The mathematical formula is as the following [3]. Formally, let \( \Omega \subset \mathbb{R}^2 \) denote a subset of the plane then anisotropic diffusion is defined as,

\[
\frac{\partial I}{\partial t} = \text{div}(c(x,y,t) \nabla I) = \nabla \cdot (c(x,y,t) \nabla I)
\]

Where, 
\( \nabla \) Denotes the gradient, 
\( \text{div}(\cdot) \) is the divergence operator and 
\( c(x,y,t) \) is the diffusion coefficient.

\( c(x,y,t) \) Controls the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. Pietro Perona and Jitendra Malik pioneered the idea of anisotropic diffusion and proposed two functions for the diffusion coefficient [4]:

\[
c(0, \nabla I) = \sigma^2 \frac{\nabla^2 I}{\cdot^2}
\]

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

And the constant \( K \) controls the sensitivity to edges and is usually chosen experimentally or as a function of the noise in the image.

3.1 SRAD
SRAD (Speckle Reducing Anisotropic Diffusion) [4]-[5] is a diffusion method for ultrasonic and radar imaging applications based on partial differential equations (PDEs). It is used to remove locally correlated noise, known as speckles, without destroying important image features. SRAD consists of several pieces of work: image extraction, continuous iterations over the image (preparation, reduction, statistics, computation 1 and computation 2) and image compression. The sequential dependency between all of these stages requires synchronization after each stage (because each stage operates on the entire image). The SRAD has the advantage of

a. One less independent parameter [7],
b. Less dependence on the norm of the gradient which can vary in the image,
c. A natural decrease of the diffusion as the estimated standard deviation of the noise decreases:

3.2 Gaussian Filter
Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. Mathematically, a Gaussian filter modifies the input signal by convolution with a Gaussian function; this transformation is also known as the Weierstrass transform [8].

\[
g(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)
\]

Where \( x \) is the distance from the origin in the horizontal axis, \( y \) is the distance from the origin in the vertical axis, and \( \sigma \) is the standard deviation of the Gaussian distribution.

3.3 Laplacian Filter
The Laplacian \( L(x,y) \) of an image with pixel intensity values \( l(x,y) \) is given by:

\[
L(x,y) = (\frac{\partial^2 l}{\partial x^2}) + (\frac{\partial^2 l}{\partial y^2})
\]

This can be calculated using a convolution filter. Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the laplacian [8].
3.3.1 Log
The Laplacian is a 2-D isotropic measure of the 2nd partial derivative of an image. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian smoothing filter in order to reduce its sensitivity to noise, and hence the two variants will be described together here. The operator normally takes a single gray level image as input and produces another gray level image as output [9]. The Laplacian \( L(x,y) \) of an image with pixel intensity values \( I(x,y) \) is given:

\[
L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}
\]

The Laplacian can be calculated using standard convolution methods. Doing things this way has two advantages:
a. Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations.
b. The LoG ('Laplacian of Gaussian') kernel can be recalculated in advance so only one convolution needs to be performed at run-time on the image.

4. FUSED METHOD
The fused method is a sequential process. The output of one phase acts as the input of the next phase. SRAD is adaptive and does not utilize hard thresholds to alter performance in homogeneous regions or in regions near edges and small features. The output of this filter is fed into another filter called the median filter. Consequently, for each pixel calculate its laplacian value with different filters- Gaussian, sobel, motion and prewitt. The output of this fused method reduces more speckles noises compare to other conventional approaches.

5. METRICS OF EVALUATION
5.1 Mean Square Error
In statistics, the mean squared error (MSE) of an estimator is to quantify the difference between values implied by an estimator and the true values of the quantity being estimated [10]. The MSE of an estimator \( \hat{\theta} \) with respect to the estimated parameter \( \theta \) is defined as,

\[
MSE(\hat{\theta}) = E[(\hat{\theta} - \theta)^2]
\]

The MSE is equal to the sum of the variance and the squared bias of the estimator.

\[
MSE(\hat{\theta}) = Var(\hat{\theta}) + (Bias(\hat{\theta},\theta))^2
\]

Table 1. Comparative analysis of liver images with the MSE values of various speckle noise removal methods

<table>
<thead>
<tr>
<th>Image</th>
<th>Normal</th>
<th>Fatty</th>
<th>Cirrhosis</th>
<th>Cyst</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRAD</td>
<td>49.501</td>
<td>16.2487</td>
<td>20.9765</td>
<td>25.9766</td>
</tr>
<tr>
<td>Average</td>
<td>105.5094</td>
<td>37.4558</td>
<td>49.9567</td>
<td>44.7208</td>
</tr>
<tr>
<td>Sobel</td>
<td>236.58</td>
<td>101.026</td>
<td>134.4821</td>
<td>169.9372</td>
</tr>
<tr>
<td>Log</td>
<td>234.0677</td>
<td>102.7856</td>
<td>134.5368</td>
<td>173.0742</td>
</tr>
<tr>
<td>Unsharp</td>
<td>75.6452</td>
<td>37.5034</td>
<td>49.6644</td>
<td>44.8865</td>
</tr>
<tr>
<td>Disk</td>
<td>55.4347</td>
<td>37.4853</td>
<td>49.6043</td>
<td>44.7006</td>
</tr>
<tr>
<td>Gaussian</td>
<td>47.5211</td>
<td>21.3819</td>
<td>27.8392</td>
<td>31.1951</td>
</tr>
<tr>
<td>Fused</td>
<td>14.6703</td>
<td>16.067</td>
<td>19.1356</td>
<td>25.3521</td>
</tr>
</tbody>
</table>

Table 2. Comparative analysis of liver images with the PSNR values of various speckle noise removal methods

<table>
<thead>
<tr>
<th>Image</th>
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<th>Cyst</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRAD</td>
<td>72.0453</td>
<td>72.0453</td>
<td>67.98</td>
<td>69.8269</td>
</tr>
<tr>
<td>Average</td>
<td>64.7912</td>
<td>64.7912</td>
<td>63.2514</td>
<td>53.6883</td>
</tr>
<tr>
<td>Sobel</td>
<td>56.1729</td>
<td>56.1729</td>
<td>51.6558</td>
<td>53.6848</td>
</tr>
<tr>
<td>Log</td>
<td>56.023</td>
<td>72.1429</td>
<td>51.497</td>
<td>62.3407</td>
</tr>
<tr>
<td>Unsharp</td>
<td>64.7802</td>
<td>64.7802</td>
<td>63.2193</td>
<td>62.2512</td>
</tr>
<tr>
<td>Disk</td>
<td>64.7844</td>
<td>64.7844</td>
<td>63.2553</td>
<td>67.3685</td>
</tr>
<tr>
<td>Gaussian</td>
<td>69.6607</td>
<td>69.6607</td>
<td>66.3799</td>
<td>67.36216</td>
</tr>
<tr>
<td>Fused</td>
<td>72.1429</td>
<td>56.023</td>
<td>68.1813</td>
<td>70.6248</td>
</tr>
</tbody>
</table>

5.2 Peak Signal to Noise Ratio (PSNR)
The PSNR is defined in logarithmic scale, in dB. It is the ratio of peak signal power to noise power [11].

\[
PSNR = 20 \log_{10} \left( \frac{MAX^2}{MSE} \right)
\]

Table 3. Comparative analysis of liver images with the RMSE values of various speckle noise removal methods

<table>
<thead>
<tr>
<th>Image</th>
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</tr>
</thead>
<tbody>
<tr>
<td>SRAD</td>
<td>4.031</td>
<td>4.11</td>
<td>5.0938</td>
<td>4.58</td>
</tr>
<tr>
<td>Average</td>
<td>6.1201</td>
<td>6.6768</td>
<td>6.6874</td>
<td>7.425</td>
</tr>
<tr>
<td>Sobel</td>
<td>10.0512</td>
<td>10.6823</td>
<td>13.036</td>
<td>11.5966</td>
</tr>
<tr>
<td>Log</td>
<td>10.1383</td>
<td>10.6728</td>
<td>13.1558</td>
<td>11.599</td>
</tr>
<tr>
<td>Unsharp</td>
<td>6.124</td>
<td>6.6823</td>
<td>6.6997</td>
<td>7.0473</td>
</tr>
<tr>
<td>Disk</td>
<td>6.1225</td>
<td>6.6783</td>
<td>6.6839</td>
<td>5.273</td>
</tr>
<tr>
<td>Gaussian</td>
<td>4.6241</td>
<td>4.9933</td>
<td>5.5853</td>
<td>4.3744</td>
</tr>
<tr>
<td>Fused</td>
<td>4.0084</td>
<td>4.2657</td>
<td>5.0351</td>
<td>4.3744</td>
</tr>
</tbody>
</table>
5.4 CoC
The Correlation of Coefficient is a method that employs tracking and image registration techniques and it allows to accurately estimating changes into images. It estimates the similarity between the original and demonized images [12]. The CoC between two images $A_{mn}$ and $B_{mn}$ is:

$$\rho = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\sum_m \sum_n (A_{mn} - \bar{A})^2 (B_{mn} - \bar{B})^2}}$$

where $A$ and $B$ are average or mean of image matrix elements.

<table>
<thead>
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<th>Cirrhosis</th>
<th>Cyst</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRAD</td>
<td>0.9222</td>
<td>0.9518</td>
<td>0.7419</td>
<td>0.967</td>
</tr>
<tr>
<td>Average</td>
<td>0.7221</td>
<td>0.6223</td>
<td>0.0688</td>
<td>0.7386</td>
</tr>
<tr>
<td>Sobel</td>
<td>0.1636</td>
<td>0.174</td>
<td>0.0596</td>
<td>0.151</td>
</tr>
<tr>
<td>Log</td>
<td>0.791</td>
<td>0.655</td>
<td>0.7414</td>
<td>0.0578</td>
</tr>
<tr>
<td>Unsharp</td>
<td>0.7212</td>
<td>0.6213</td>
<td>0.7416</td>
<td>0.738</td>
</tr>
<tr>
<td>Gaussian</td>
<td>0.8378</td>
<td>0.7431</td>
<td>0.9064</td>
<td>0.8414</td>
</tr>
<tr>
<td>Fused</td>
<td>0.9899</td>
<td>0.9722</td>
<td>0.9457</td>
<td>0.8952</td>
</tr>
</tbody>
</table>

7. REFERENCES