Improved Despeckle Filtering Technique for Liver Cirrhosis US Images

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Abstract

The liver ultrasonic (US) images suffer from inherent speckle noise, degrading the image quality; thereby, affecting human interpretation and also reducing the accuracy in computer-assisted diagnostic techniques. In this paper, we propose an improved despeckle filtering technique by combining, maximum homogeneity over a pixel neighborhood filtering (MHON) and speckle-reducing anisotropic diffusion filtering (SRAD) using a binary classifier map (BCM). The textural and fine details of residual image are denoised by SRAD filtering. The SRAD filter denoised image and MHON filter denoised image combines to attain BCM. A BCM is generated by examining the local coefficient of dispersion (CoD) assessed using a kernel with the one obtained from a specific region. The proposed method is evaluated on clinical US image set of liver, by assessing the quality factors PSNR, SNR, ISC, LMSE and EPI. Results are compared with specified algorithms separately while accomplishing for proposed method.

Keywords: Liver US image, MHON, SRAD, UQI, EPI, and LMSE.

1. Introduction

Various imaging modalities are used for diagnosis of internal organs of the human body. A real time, noninvasive and non-ionizing technique is Ultrasound (US) imaging technique [1, 12]. The US images of soft tissue in human body are corrupted due to several noises such as additive noise, US device noise, multiplicative noise (speckle) etc. However, the effect of granular or speckle noise is foremost in terms of visual quality of US images [2,11]. Speckle noise degrades the quality of the image. Denoising of US images is significant in post processing operations such as compression, segmentation.

Denoising using Lee [3], Frost [4] and Kuan [5] spatial domain filters are popular, as denoising is mainly based upon the local statistics of image. The performance of filters always reliant on the size and shape of selected filter kernel to attain a good denoising capability in specific regions of image [10]. The speckle reduction and edge preservation in the images degraded by additive noise is achieved by anisotropic diffusion method proposed by Perona& Malik [6]. An anisotropic diffusion method, speckle reducing anisotropic diffusion (SRAD) method based on local gradient magnitude is proposed by Yu & Acton [7].

The filtering methods with in the discussed literature are adequate for speckle reduction; be that as it may be, they are computationally intensive as contrasted with the proposed method. The denoised images obtained from MHON and SRAD are mapped using BCM to reconstruct the final denoised image. BCM is made in light of CoD[13]. The paper is organized as follows: Part I gives the literature for methods used in speckle denoising. Part II describes the proposed strategy of speckle noise reduction.

In part III experimental results and discussions are presented, followed by conclusion as part IV.

2. Proposed method

The uniqueness of the proposed method is to enhance the quality of the denoised image by combining the nonlinear filtering with diffusion filter. The nonlinear filter- MHON, has good behavior in textural region and detail area of the image. The diffusion filter-SRAD, removes texture similar to noise removal of the image. The proposed denoising technique illustrated in figure 1 and is presented in the next sections.

![Fig. 1: Illustration of the proposed method](image-url)
Maximum homogeneity over a pixel neighborhood filtering (MHON)

The MHON is an automatic nonlinear filtering technique [9, 10]. An estimation of the foremost homogeneous neighborhood around every pixel is considered by the pixels that belong to processed neighborhood in a determined homogenous area. The output image, \( f_{ij} \) is obtained by using equation 1.

\[
f_{ij} = \frac{c_i g_{ij}}{\sum_i g_{ij}} \text{ with } \left\{ \begin{array}{l} c_i = 1 \text{ if } (1 - 2 \sigma_a) \leq g_{ij} \leq (1 + 2 \sigma_a) \nonumber \\ c_i = 0 \quad \text{otherwise} \end{array} \right. \tag{1}
\]

Speckle-reducing anisotropic diffusion filtering (SRAD)

The WLV is used to find the location of texture of residual image (obtained by subtracting the noisy image and primarily denoised image) and is calculated using equation 2 [10].

\[
\sigma^2 = \frac{1}{N^2} \sum_{x=-N/2}^{N/2} \sum_{y=-N/2}^{N/2} [I(x,y) - \bar{I}(x,y)]^2 \cdot W_{XY}(i,j)
\tag{2}
\]

Where \( \bar{I}(x,y) \) is the median of the graylavels in the \( N^2 \) neighborhood window \( W_{XY}(i,j) \) is the weight of \( (X,Y) \) that is determined with 2D Guassiankernel in the neighborhood window. A binary mask corresponding the textual region is obtained using morphological operator. Multiplying the binary mask to the residual image reaches textural region. The edges of homogenous textual region is retained in the residual image using an anisotropic diffusion filter –SRAD, by simultaneous contrast enhancement and noise reduction [9, 10].

The gradient based edge detector, \( c_d(\nabla g) \) in anisotropic diffusion PDE is replaced with the instantaneous coefficient of variation, \( c_{srad}(|\nabla g|) \) for speckle reduction. The SRAD speckle reducing anisotropic diffusion filter, uses two apparently different methods, viz., the Lee and the Frost diffusion filters. The output image function (3) is obtained by extending the probability distribution estimations forms of the despeckle filter and is given by:

\[
f_{ij} = g_{ij} + \frac{1}{\eta_a} \text{div} \left( c_{srad}(|\nabla g|) \nabla g_{ij} \right)
\tag{3}
\]

The diffusion coefficient for the speckle anisotropic diffusion, \( c_{srad}(|\nabla g|) \), is:

\[
c_{srad}(|\nabla g|) = \frac{1}{\eta_a} \left( \frac{\nabla g_{ij}^2}{g_{ij}^2} - \frac{2}{\nabla g_{ij}^2} \left( \frac{\nabla g_{ij}}{g_{ij}} \right)^2 \right)
\tag{4}
\]

The required condition is \( c_{srad}(|\nabla g|) \geq 0 \).

Formation of bilinear classifier map (BCM)

The ultimate denoised image is reconstructed by mapping the textural features of MHON and SRAD filters’ image. BCM is acquired by looking at neighbourhood CoD got over all pixel of image with the one got from chosen homogeneous locale [13]. For the homogeneous region, CoD is far less when contrasted with the edge locale. For the edge region, CoD is high and low for homogeneous region. The BCM is formed conventionally as follows.

1. For the order of pixels, initial a homogeneous region is picked in the speckled image and the proportion of variance to mean is figured (T).
2. Local CoD of \( T(i,j) \) is registered utilizing Kernel of size \( W \times W \) traveling through all pixels of the noisy image.
3. A pixel is named homogeneous area pixel if the esteem \( T(i,j) \) is not as much as equivalent to \( T \). Something else, the pixel lies in edge region.
4. For a pixel \( (i,j) \) if the window is homogenous then a comparing dark pixel is picked in outline comparatively for edge window while pixel esteems are picked in map. At last, a map comprising of highly contrasting qualities are acquired.

Finally the ultimate denoised image is obtained according to the information obtained in BCM. The two denoised images acquired subsequent to applying MHON and SRAD filters on the speckle corrupted image alluded to as denoised image1 and denoised image2 separately. These filtered images are mapped by the data acquired in BCM; For a dark pixel in BCM the relating picture pixel in denoised image1 and for a white pixel in BCM comparing picture pixel in denoised image2 are held to get final reconstructed image.

### 3. Performance Parameters and Experimental Results

**Performance parameters**

For performance analysis, several parameters such as Signal to Noise Ratio (SNR), Peak Signal to Noise ratio (PSNR), Image Structural Content (ISC), Laplacian Mean Square Error (LMSE) and Edge Preserving Index (EPI) are used. The real image of a liver US image is shown in figure 2.

![US image of the liver](image)

**Signal to Noise Ratio (SNR):** The SNR is calculated over a N x M image, and is calculated by

\[
\text{SNR} = 10 \log_{10} \frac{\sum_i \sum_j (g_{ij} + f_{ij})}{\sum_i \sum_j (g_{ij} - f_{ij})^2}
\tag{5}
\]

**Peak Signal to Noise Ratio (PSNR):** PSNR measures the image fidelity, resembling the closeness of the despeckle image to the original image. The PSNR is high for well transformed image and low for a poorly transformed image.

\[
\text{PSNR} = -10 \log_{10} \frac{\text{MSE}}{g_{\text{max}}^2}
\tag{6}
\]

Where, \( g_{\text{max}} \) is the maximum intensity in the unfiltered image and MSE is the Mean Square Error given by

\[
\text{MSE} = \frac{1}{NM} \sum_{i=1}^{M} \sum_{j=1}^{N} (g_{ij} - f_{ij})^2
\tag{7}
\]

**Image Structural Content (ISC):** The image structural content of the despeckle image is given by

\[
\text{ISC} = \frac{\sum_i \sum_j (g_{ij} - f_{ij})}{\sum_i \sum_j f_{ij}}
\tag{8}
\]
The quality of the image is indirectly proportional to the ISC i.e., larger the values of ISC lesser the image quality.

**Laplacian Mean Square error (LMSE):** The edge measurement of the image is based on LMSE. Poor quality of the image refers to larger LMSE values. The LMSE is obtained from

$$\text{LMSE} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} [g(i,j) - \bar{g}(i,j)]^2}{\sum_{i=1}^{N} \sum_{j=1}^{M} [f(i,j)]^2}$$  \hspace{1cm} (9)

Where, $L$ is the Laplacian operator which is defined as

$$L(i,j) = g(i+1,j) + g(i-1,j) + g(i,j+1) + g(i,j-1) - 4g(i,j)$$  \hspace{1cm} (10)

**Edge Preserving Index (EPI):** The proposed method mainly depends upon the edge preserving index of the denoised image which is given by

$$\text{EPI} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} [\Delta g_{i,j} - \Delta \bar{g}_{i,j}] (\Delta f_{i,j} - \Delta \bar{f}_{i,j})}{\sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M} [\Delta g_{i,j} - \Delta \bar{g}_{i,j}]^2} \times \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M} [\Delta f_{i,j} - \Delta \bar{f}_{i,j}]^2}}$$  \hspace{1cm} (11)

$\Delta g_{i,j}$ and $\Delta f_{i,j}$ are the outputs of $g_{i,j}$ and $f_{i,j}$ after applying by a 3x3 Laplacian operator and high pass filter, and $\Delta \bar{g}_{i,j}$ and $\Delta \bar{f}_{i,j}$ are the mean values of $\Delta g_{i,j}$ and $\Delta f_{i,j}$. EPI is known as the correlation factor to the original image. Closer the value of EPI to one, closest the denoised image to the original.

**Experimental analysis**

The performance of the proposed method is tested and compared with test results obtained from despeckle filter MHON and despeckle filter SRAD filtering individually. The evaluation test was performed in a unified tool kit that incorporates image despeckle filtering (IDF) [8], texture analysis and image quality assessments which is developed on computational software MATLAB®. The software, is based on a graphical user interface (GUI).

Cirrhosis affected liver images acquired from the two different US video output (8 bits grayscale codec) are used in experiment; US video1 - Image-I with the center frequency 2.22 MHz, Spatial resolution 0.71 mm/pixel & temporal resolution 25fps and US video2 - Image-II with the center frequency 2.0 MHz, spatial resolution 0.40 mm/pixel & temporal resolution 16fps are used for experimentation. The images acquired are collected from volunteers at the Radiology Department of Geneva University Hospital, Switzerland [14]. These images are standardized and confirmed by an expert doctor were utilized for experimental analysis.

Figures 3 (a) – (d) and figures 5(a) – (d) presents the real US images of liver images with no real noise free is used for qualitative experimental analysis. From the visual review it can be seen that the quality of denoised image obtained using MHON filter is poor among all images. Quality of images obtained after applying WLV, morphological operation and then SRAD filter gives better visibility having higher contrast. The proposed filter is almost the same with better visibility and best in terms of edge detail preservation; even tough, there is a loss of minor details present in the one obtained using SRAD filter.

The statistical textural features are evaluated for image-I & II, shown in table 1 and 3. To quantify the performance of the proposed algorithm, various image quality metrics are evaluated for figures 3 & 5 (a, b, c and d) and tabulated in table 2 and 4 respectively.

**Table 1:** Statistical Textural Features of the liver US image-I specified in Figure 3

<table>
<thead>
<tr>
<th>Feature</th>
<th>Original Image</th>
<th>HMON Filter</th>
<th>SRAD Filter</th>
<th>Proposed filtering method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>20.011</td>
<td>20.838</td>
<td>19.934</td>
<td>39.795</td>
</tr>
<tr>
<td>Median</td>
<td>8.487</td>
<td>4.487</td>
<td>8.488</td>
<td>18.129</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>15.403</td>
<td>21.497</td>
<td>14.655</td>
<td>29.046</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.845</td>
<td>1.832</td>
<td>1.481</td>
<td>1.404</td>
</tr>
<tr>
<td>Coarseness</td>
<td>32.376</td>
<td>23.423</td>
<td>50.979</td>
<td>24.809</td>
</tr>
<tr>
<td>Contrast</td>
<td>6.157</td>
<td>8.530</td>
<td>3.926</td>
<td>7.512</td>
</tr>
<tr>
<td>Periodicity</td>
<td>0.623</td>
<td>0.622</td>
<td>0.758</td>
<td>0.739</td>
</tr>
<tr>
<td>Roughness</td>
<td>2.456</td>
<td>2.454</td>
<td>2.105</td>
<td>2.185</td>
</tr>
</tbody>
</table>

**Table 2:** Performance parameters for various filtering of Image-I

<table>
<thead>
<tr>
<th>Performance parameters</th>
<th>HMON Filter</th>
<th>SRAD Filter</th>
<th>Proposed filtering method</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR - Signal to Noise Ratio</td>
<td>22.845</td>
<td>16.062</td>
<td>15.3488</td>
</tr>
<tr>
<td>PSNR - Peak Signal to Noise Ratio</td>
<td>40.370</td>
<td>32.696</td>
<td>39.4941</td>
</tr>
<tr>
<td>UQI - Universal Quality Index</td>
<td>0.474</td>
<td>0.866</td>
<td>0.95265</td>
</tr>
<tr>
<td>EPI – Edge Preserving Index</td>
<td>0.967</td>
<td>0.894</td>
<td>0.97329</td>
</tr>
<tr>
<td>ISC – Image Structural Content</td>
<td>1.042</td>
<td>0.711</td>
<td>0.629</td>
</tr>
<tr>
<td>LMSE - Laplacian Mean Square Error</td>
<td>0.698</td>
<td>0.168</td>
<td>0.16628</td>
</tr>
</tbody>
</table>
The statistical textural features for proposed method is less comparable to the despeckle filters, MHON and SRAD. The performance metrics for proposed method filtered image(s) are enhanced, leading to better visibility by DE-speckling, figure 3 (d) and figure 5 (d). However, the correlation factor EPI for the denoised image(s) filtered through the proposed method is closer to original image, figure 4 and 6. The LMS error is relatively small, figure 7 for the denoised images through proposed method to that of other methods discussed in the paper. This marks the proposed method better than the filtering methods filtering ways mentioned within the paper.

4. Conclusion

Alternative denoising procedure for speckle noise reduction in liver cirrhosis US images was introduced in this paper. This method is the balance of two well-known filters, i.e., MHON and SRAD. CoD parameter is utilized to order the image pixels into homogeneous and edge locales by framing a BCM. Investigations
were led on liver US images utilizing IDF tool kit and both target
and in addition subjective quality assessment of denoised images
was displayed. Real liver images are taken from US video
sequences of the volunteers, at the Radiology Department
of Geneva University Hospital, Switzerland, are used for
investigating the visual examination of denoising algorithms. The
conclusions got from the investigation demonstrates the viability
of the proposed work over MHON and SRAD filters, both for
noise reduction and preserving the edges. The aftereffects of
proposed technique additionally prescribes in extracting optimal
features in liver malignancy discovery and classification.

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